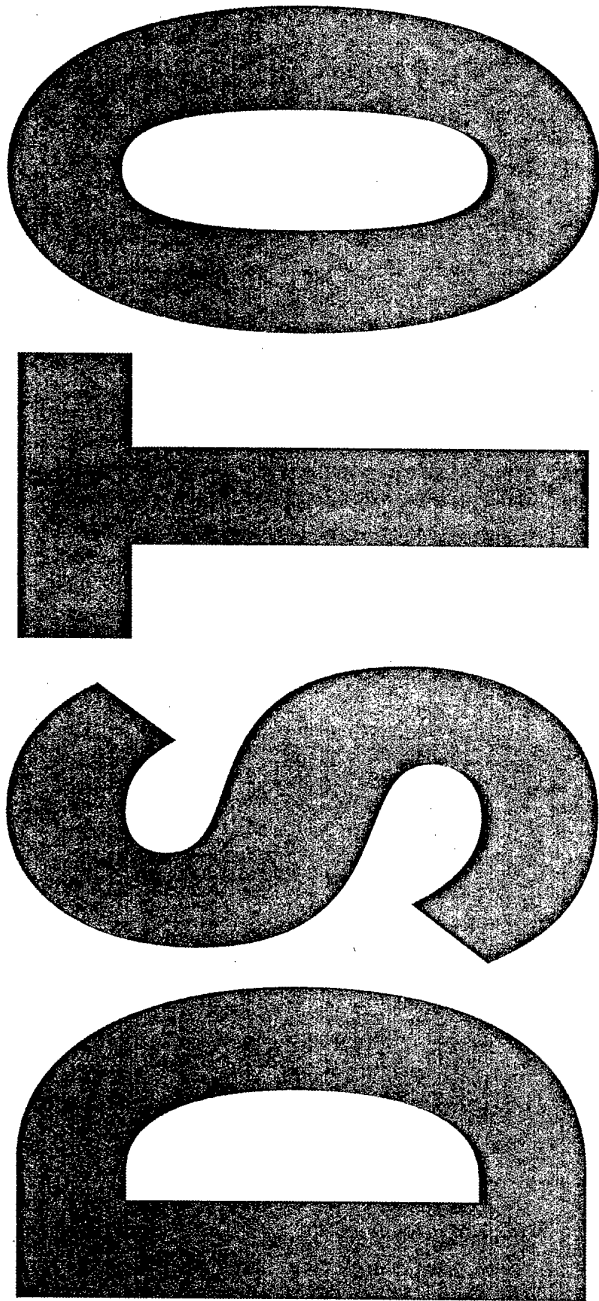**Australian Government**

Department of Defence

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Effects-Based Operations: Simulations with Cellular Automata

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ABSTRACT

In this report I show how simulations through cellular automata can be used to answer Effects-Based Operations (EBO) related questions. Such simulations provide effective tools to investigate the two themes that lie at the heart of the EBO paradigm which are that (a) the operations be holistic –treat the adversary as a complex system with interconnected political, military, economic and social facets and (b) that the immediate and higher order effects of the actions be gauged and exploited. This report focuses on the effects of actions against an adversary. How to integrate the friendly national capabilities for a whole of government approach has not been discussed here. An effects-based strategy is formulated which is a minimal strategy in the sense that it provides a mode of interdiction whose cascading effects are strong enough to compel the enemy to abandon hostilities while not driving the adversary to a point where its military, and non-military social systems become unstable. The parameters governing this strategy are identified and simulations conducted to elicit the parameter values that produce the desired effects.

RELEASE LIMITATION

Effects-Based Operations:
Simulations with Cellular Automata

Executive Summary

Effects-Based Operations (EBO) is a phrase used to represent a host of concepts permeating current military thinking regarding planning and operations. These concepts are still evolving, and much literature exists espousing different points of view. These differences exist because of the different aspects that have been emphasised by different proponents. Nonetheless there is a universal agreement that, for meaningful EBO analysis, the adversary should be treated as an integrated complex system. Treating the adversary as an integrated complex system has the disadvantage that as yet there exist no generally applicable analytical methods to conduct other than superficial analysis. Hence although a number of interesting doctrines and a variety of novel strategies for effects-based planning and operations have been put forward, what has been missing is a sound framework to conduct experiments, to put these strategies to test. A framework to formulate these strategies systematically and conduct 'what if' experiments is needed. The main contribution of this report lies in establishing that cellular automata can provide the tools needed for such experimentation.

In this report I adopt the following basic framework. An operation will be called an *effects-based operation* if it satisfies the following two *necessary* criteria:

1. The operation is *holistic*. It takes into account all the factors – political, military and socio-economic - of the adversary system together with the complex interactions between them.

2. The operation *gauges and exploits higher order effects*, in addition to the immediate effects, of the actions taken.

The report is essentially an elaboration and investigation of these two criteria, and focuses on achieving effects on an adversary.

The document deals with two opposing sides A and K where A is viewed as the friendly side while K constitutes the adversary. Cellular automata are used to simulate the evolution of an adopted scenario where A's Military Strategic Objectives are to undermine K's will and ability and neutralise its leadership's capacity to conduct offensive military operations.

An effects-based strategy is formulated where it is argued that instead of seeking the traditional purely militaristic solution A should respond to K's actions on all fronts using military, diplomatic and socio-economic means. Instead of delivering large military disturbances to K, A should impart a large number of small disturbances to K's military, political and socio-economic establishments. These disturbances would be given randomly, in an opportunistic manner, and would produce random and minor

first order effects which may go unnoticed by K. However the higher order effects of these small disturbances will accumulate to eventually produce large-scale cascading avalanches in an unpredictable fashion. This will catch K's leadership unawares, severely undermining its *will and ability*.

Simulations through cellular automata are conducted to evaluate the above strategy. The cells of the automaton represent K's political, military and socio-economic elements. The automaton is allowed to evolve while being governed by the following three factors:

A. The A forces *interdict* the elements of K continually as time develops.

B. K reacts to the interdictions trying to restore the affected elements. This is accomplished through an *averaging rule*, which essentially means that when an element is interdicted its neighbours get together to restore its effectiveness to an extent that is possible given their own levels of effectiveness.

C. Some K elements also increase their effectiveness spontaneously through *creativity and ingenuity* as the situation develops.

These factors are specified through quantitative parameters.

Cascading effects of *interdictions* are visualized as avalanches in the automata. These are avalanches of degradations in the effectiveness of K's elements. A *minimal strategy* is then formulated which aims at achieving a degrading avalanche of a certain magnitude that would be severe enough to compel K to abandon hostilities, but not be so overwhelming as to trigger instability in its military and socio-political systems, leading to effects not conducive to A's strategic interests. The parameters governing this strategy are identified and simulations conducted to elicit the parameter values that produce the desired effects.

An essential lesson learnt during the analysis is that conducting EBO requires a deep knowledge of the adversary culture across all of its facets, political, military and socio-economic. This is not surprising considering the fact that effects-based operations intend to establish dominance over the adversary not just in the physical domains, but more importantly in the behavioural domains also. Notwithstanding this, the framework for simulation presented here would enable an analyst to conduct 'what if' experiments with plausible values for parameters representing cultural and other facets. This will provide him with a holistic understanding of various patterns of cascading effects, the essence of any effects-based operations.

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Contents

1. Introduction

Effects-Based Operations (EBO) is a phrase used to represent a host of concepts permeating current military thinking regarding planning and operations. All these concepts contain at their kernel one or both of the two central paradigms:
- a holistic view of the situation involving not only its military aspects but also the connected economic, political and social aspects and
- an emphasis on not being confined to the immediate effects of a military action but also to gauge and exploit higher order and emergent effects.

At this point one may wonder as to what makes these paradigms novel. Commanders have always planned with objectives and effects in their mind and good commanders have always known that war is just another form, albeit an extreme form, of political and economic engagement. Nations have waged war not to unleash death and destruction, the immediate effects, but to achieve ultimate political and economic goals. What is new is that EBO or the resulting Effects-Based Strategy (EBS)[1] is not military centric. The guiding principle here is - do not be confined to military operations while looking out for political and economic fallouts. In fact, proponents of EBO treat the adversary as a complex system with interconnected economic, military, political and social facets. Hence any action against the adversary should directly affect the entire spectrum spanned by these facets. Again this is not new. Past masters well understood the need for planning operations that could affect all the facets of the adversary system. But except for some intuitive reasoning, they never had the tools to carry out such planning systematically. We do not have the tools now either, yet there is an expectation that present capabilities for processing information will soon deliver such tools to military planners. The present work is an attempt to realise this goal.

Conducting EBO requires a fundamental change in strategic thinking. In Section-2, I conduct a brief review to bring forth the kind of changes being advocated by various EBO thinkers. As we will see there exists a lot of commonality among the existing points of view.

Treating the adversary as an integrated complex system has the disadvantage that, as yet there exist no generally applicable analytical methods to conduct other than superficial analysis. This is precisely why the method of simulations has been advocated in Section-3. In this section I introduce the concept of cellular automata to serve as our device for simulation. A scenario detailing a hostile situation between the adversary and the friendly forces is then constructed and the time evolution of this scenario is simulated through the evolution of the representative cellular automaton.

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[1] Forestier (2001) writes: "Turning briefly to taxonomy, the term 'EBO' is not an overly useful one in considering the intent of national strategy. In fact the 'operations' element of the term is downright misleading if applied at the national strategic level. I suggest a better term from the Australian perspective would be 'Effects-Based Strategy' (EBS). .... This taxonomy has EBS effected through EBO, which is logical."

Since a major aim of any such exercise is to understand how an adversary system can be steered through EBO to a state where it ceases to be a threat, I establish the basic premises for an effects-based strategy in Section-4. This is a minimal strategy in the sense that its implementation generates just enough compelling reasons for the adversary to abandon hostile activities against the friendly forces within a given period of time. This strategy is then simulated through cellular automata, for the adopted scenario, and numerical values for the parameters governing the strategy are gleaned from simulation results. The primary focus here has been to simulate the effects of actions against an adversary's military and non-military systems. How to integrate the friendly national capabilities for a whole of government approach has not been discussed here.

2. EBO, A Working Review

What defines EBO? Much literature exists espousing different points of view and it is encouraging to note that there exists a lot of commonality among these points of view. Differences exist because of the different aspects that have been emphasised by different proponents. EBO is still an evolving concept, it would therefore be detrimental to prescribe a rigorous definition. Rather one should encourage a way of thinking that accommodates the commonality among the different views and has scope for growth. With that in mind, let us conduct a brief review that is enough to familiarise ourselves with the main ideas.

As a large part of EBO thinking has originated from US military personnel and institutions, it would be appropriate to start with the prescription offered by the U.S. Joint Forces Command.

> This defines EBO as a process for obtaining a desired strategic outcome or "effect" on the enemy, through the synergistic, multiplicative, and cumulative application of the full range of military and nonmilitary capabilities at the tactical, operational, and strategic levels [JFCOM].

Here the emphasis is on the synergistic application of military and nonmilitary capabilities to obtain desired effects. What effects are desired? This has been emphasized comprehensively by the US Naval War College as follows [See Forestier, 2001 and references therein]:

> Effects-Based Operations seek to defeat our enemy's strategy and resolve vice merely attrite [sic] his armed forces, and although this idea is not new, new information technologies are enabling us to know our enemy, our enemy's strategy and operational doctrine, and our enemy's centers [sic] of gravity better. Our increased understanding of the complex inter-relationships that exist between our adversary's military, economic and political realms, will enable the development of

an operational plan that will produce effects that can manipulate our opponents belief and reason domains in addition to defeating our enemy's physical forces

Here the emphasis is on defeating the enemy's strategy rather than its forces. Manipulating the enemy's belief system so that it views continuation of aggression as futile and adopts a course of action that leads to a situation desired by the friendly side. A rather feisty restatement of these notions from an Australian (Air Force) point of view is provided by Forestier and Thiele [2001]

Air Force and the other national security actors should cooperatively build adaptive systems and educate our people to exploit them. The aim, from a national protection and force projection perspective, is to ensure that Australia is seen as a 'prickly echidna-tasmanian devil cross-breed - an Aussie mongrel in the security sense - essentially non-aggressive, but capable in defence, and downright nasty in attack. An antagonist can never be precisely sure of how we will respond if provoked, but knows we have significant operational breadth to draw from, and can orchestrate a variety of parallel responses. He knows we will be targeting for effect. Our aim is stability and peace, but also to be capable of quick and decisive conflict resolution if that is what is required. Giving our forces an asymmetric advantage by having the ability to quickly adapt in unique ways, and having that ability recognised and respected, is the proposition that Air Force wishes to promote. That will be the Australian way of reassurance, deterrence and war-fighting.

Such views are often attacked by critics on the ground that these notions downgrade target-based operations like destruction of the enemy forces and occupation of its territories. Proponents, therefore, often hasten to add that they view EBO as an expansion rather than abolition of the classical strategy of attrition and occupation. Attrition and occupation still form an important part of the strategy but are only as important as the strategy for targeting the enemy's economic basis and political standing.

EBO, as a synergistic application of military and non-military capabilities to achieve first order and higher order effects, has also been emphasised by Davis [2001] who defines:

Effects-based operations are operations conceived and planned in a systems framework that considers the full range of direct, indirect, and cascading effects, which may – with different degrees of probability – be achieved by the application of military, diplomatic, psychological, and economic instruments.

Though similar in spirit to the previous definitions, note the emphasis on *systems framework, cascading effects* and the explicit mention of *probability*. Let us commit these factors to our memory, for the results we find in this report are answers to EBO related questions expressed in terms of these factors.

Davis then takes the next step to identify a number of macroscopic factors that any satisfactory EBO analysis should take into account. These include both physical and behavioural targets such as:

Physical targets – tanks, soldiers, military HQs and supporting industry and infrastructure

Behavioural targets – enemy perceptions, social behaviour, decision making paradigms etc. or the soft factors as they are often euphemistically called.

Davis correctly observes that current mainstream analysis addresses only a small part of what EBO entails. A proper framework for modelling and simulation and analytical thinking which can model, simulate and analyse all the relevant macroscopic factors in an integrated and correlated fashion is according to Davis, a very distant dream.

Another notion that also becomes abundantly clear from the literature is that implementing EBO not only requires the above discussed analysis of the adversary system, but also a substantial reorganisation of the friendly system and capabilities. Reorganisations that can hone the friendly system to successfully undertake EBO. In this paper we analyse the adversary system from an EBO point of view. How the friendly military capabilities are employed – how political, economic and military instruments together with information warfare capabilities can be employed in an integrated and adaptable fashion to bear down on the adversary – has not been discussed here. These points have been discussed by a number of investigators [EBO (2003), Forestier (2001, 2001a)] from an Australian point of view while Saunders-Newton & Frank [2002] espouse an American perspective.

Further insight into EBO can be gleaned from the excellent Military Operations Research Society website [MORS], which lists a number of interesting papers.

3. A Framework for Simulation

With the knowledge gained through the brief review let me adopt the following basic framework to guide further analyses. An operation will be called an *effects-based operation* if it satisfies the following two *necessary* criteria:

1. The operation is *holistic*. It takes into account all the factors – political, military and socio-economic (*pol-mil-sec*) - of the adversary system together with the complex interactions between them.

2. The operation *gauges and exploits higher order effects,* in addition to the immediate effects, of the actions taken. Given an action its effects at the next time step constitute its first order or immediate effects while those at subsequent time steps make up the increasingly higher order effects. In other words an action initiates a ripple that propagates through the system over time. What is more this ripple

combines with other such ripples emanating from preceding and successive actions giving rise to cascading and emergent effects.

The rest of the report is essentially an elaboration and investigation of these two criteria, and as mentioned earlier, focuses on achieving effects on an adversary.

The knowledge gained through the review also brought home the fact that current analytical methods are not good enough to answer EBO related questions. This has been pointed out by almost everyone who has written on the subject. Instead of rewriting the same again let me just cite one such comment.

> "A central concern is that the current suite of analytic tools cannot represent all the aspects that interest political and military leaders and allow their actions to remain mutually supportive. The current tools can generate logistical and targeting plans that make the best use of available resources, but they cannot determine the degree to which a particular targeting scheme will influence the will of an adversary or the emergence of post-conflict order. Nor can the current tools generate insight into whether a desired outcome can be achieved by using national capabilities other than military force. Nor can they evaluate the probable results using differing mixtures of force and diplomacy. A new set of tools is necessary to support and implement new strategies" [Saunders-Newton & Frank (2002)].

As a first step therefore one has to develop the kind of new tools alluded to in the above remark. This section lays the foundation.

What kind of analysis are we good at? Newtonian, according to the military operations research community. This is a reductionist approach. Here we identify the macroscopic factors pertinent to the problem - for example the factors identified by Davis [2001] – and then drill down through such factors to identify their microscopic elements. If we can identify simple enough microscopic elements, it becomes possible to model these elements. The next question is what do we expect from our models? Essentially we want our models to be *predictive*, and two requirements stand out in this regard. We want to predict the future states of the system given a course of evolution and the other way round i.e., given a desired future state we want to determine in advance the optimal strategy to attain that state. Hence, we have to integrate the microscopic models to obtain a model of the system as a whole and then fathom the evolution of the system over time. This is where our difficulties lie. Once the number of microscopic elements becomes large our analytical methods generally get overwhelmed and provide little holistic analysis. In fact the model becomes as intractable as the real world system being modelled.

The basic problem is essentially the following: it is difficult to find an overall model description of a system, even when reasonably complete information about its microscopic components and their interactions is known. This modelling gap or this inability to translate microscopic level knowledge into the macroscopic level is a

fundamental limitation to the analytical approach to science[2]. This is why computer simulations are so vital to the understanding of systems with many components. We cannot formulate theories, but given the vast computing power that is readily available, we can always simulate the system, watch it evolve, and hence gain insights into its workings.

The methods of *agent-based-modelling* provide excellent tools for the kind of bottom-up integration we are interested in. This essentially involves creating computational models that include a large number of individual agents. These individual agents are characterized through defining properties and interact with agents in their neighbourhood. Knowing the individual character and the nature of local interactions one can easily compute the next step in local evolution. Given enough computing power one can compute for every individual agent synchronously to obtain the next step in the global evolution. Repeating this process over and over again it is possible to watch the patterns in global evolution through a graphic interface. A very fruitful way for realising such agent-based-modelling is through *cellular automata*. These are fast becoming an attractive tool for scientific endeavour[3]. Let me proceed by introducing these automata.

3.1 Cellular Automata

Cellular automata are discrete dynamical systems whose evolution is completely specified by specifying the states of its atomic elements and their local interactions. They can therefore be regarded as discrete idealizations of partial differential equations. The hallmark of this approach is to prescribe simple models for the atomic elements and their interactions. This simplicity at the atomic level nonetheless produces complex global behaviour as the automata evolves through the interactions of its many elements.

The following basic features specifies a cellular automaton [Wolfram (1994), Hegselmann and Flache (1998), Casti (1992), Toffoli & Margolus (1987)]

- The automaton consists of a regular *D-dimensional* lattice of sites.
- Each cite or *cell* in the automaton can be in one of a finite number of specified states.
- The automaton evolves over a succession of *discrete time steps.*
- The states of all the cells in the automaton are updated *synchronously* at each time step.

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[2] This is what the theory of complex systems is all about. There exists a vast literature on this subject; Edmonds [1999] provides a comprehensive review and an excellent discussion.

[3] First introduced by J. von Neumann (*Theory of Self-Reproducing Automata* Univ. of Illinois Press, 1966) interest in Cellular Automata was renewed in recent times when the journal Physica (*Physica* **10D** 1984) devoted an entire issue to the topic demonstrating its versatility.

- Cells change their states according to *local* rules. In other words the state transition rules for cells take into account the states of the cell and those of its neighbours only.

Figure 3.1 depicts a 2-dimensional cellular automaton where the cells are arranged to form a 25×25 square lattice, different states of a cell are colour coded to different hue with different shades.

Since state transition rules for cells take into account the states of the cell and those of its neighbours it is necessary to specify the neighbourhood configuration. Two most commonly used neighbourhood for a 2-dimensional cellular automaton are the
- *von Neumann neighbourhood* where a cell C has four neighbours E, N, W and S as depicted in Figure 3-2 and the
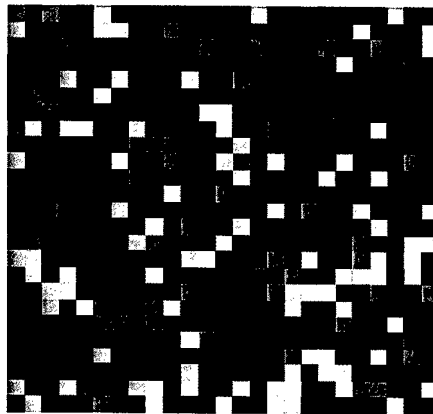- *Moore neighbourhood* where a cell C has eight neighbours as depicted in Figure 3-3.

Figure 3-1: A 2-dimensional cellular automaton where the cells are arranged to form a 25×25 square lattice, different states of a cell are colour coded to different hue with different shades.
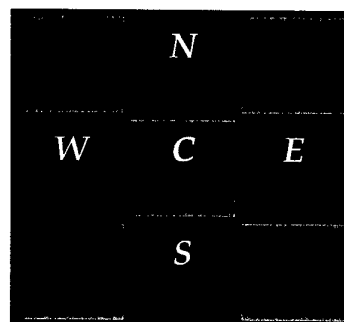

Figure 3-2:The von Neumann neighbourhood where a cell **C** *has 4 neighbours* **E, N, W** *and* **S**
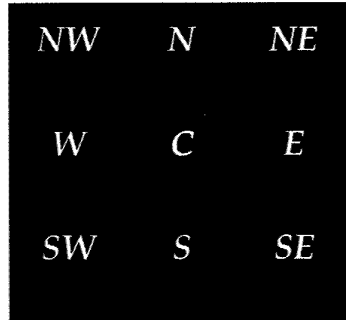
Figure 3-3: The Moore neighbourhood where a cell C has 8 neighbours E, NE, N, NW, W, SW, S and SE.

There is one difficulty with the flat structure of the lattice shown in Figure 3-1. Cells at the left edge have no *western* neighbours while those at the right edge are neighbour-less on the *eastern* side. Similar fate befalls the cells at the upper and lower edges who lack neighbours respectively on the *northern* and *southern* sides. To rectify this the left edge of the lattice is pasted to the right edge and the top edge to the bottom. This converts the flat lattice in Figure 3-1 to a lattice in the shape of a torus as shown in Figure 3-4. All cells now acquire the full quota of neighbours.
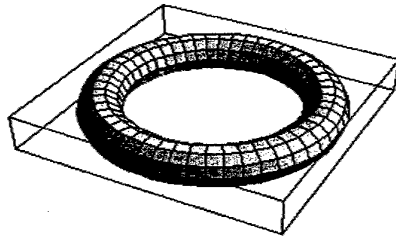

Figure 3-4: A two dimensional cellular automaton with the left edge of the lattice pasted to the right edge and the top edge to the bottom.

If τ represents the transition rule for cell states and $c(t)$ represents the state of the cell C at the time step t with similar notations for other cells, then the state of the cell C at the next time step $t+1$, for the *von Neumann neighbourhood*, is given by

$$c(t+1) = \tau[c(t), e(t), n(t), w(t), s(t)]. \qquad (3.1)$$

This rule is applied synchronously and repeatedly to all cells in the automaton resulting in its time evolution. This rule can be very simple or complicated. The interesting fact is that cellular automata driven by innocuous local rules often exhibit very complicated global behaviour. We owe much of our knowledge regarding the nature of cellular automata and their applications to the seminal work carried out by Wolfram [1994, 2002]. On the application side cellular automata have proved to be very

versatile. They have been used to generate land combat models [Lauren (2000)]. More interestingly they have also been used to model aspects of social sciences and provide valuable insight into social processes otherwise not amenable to theoretical analysis. Works of this latter kind are closer in spirit to our present endeavour. Hegselmann[1998] gives a very good review of cellular automata based modelling applied to social sciences. Another rich source is the book by Gaylord and D'Andria[1998], while in a companion book Gaylord and Nishidate [1996] discuss applications of cellular automata to the physical sciences. Both these books also show the reader how to obtain computer simulations of cellular automata using *Mathematica* - the present work adopts this mode of simulation.

3.2 Cellular Automata Simulations of the Adversary Pol-Mil-Sec Systems

Having chosen cellular automata as our paradigm for simulation, the next step is rather obvious – to construct models of the adversary pol-mil-sec systems and watch these automata run long enough until they reveal their global behaviour. This can be done repeatedly starting from varied initial conditions and the results obtained will provide data for statistical analysis. To start the process we need first to identify the basic elements of the adversary pol-mil-sec system – these would be represented as cells in the automata. These elements are identified keeping in mind the nature of the investigation we want to conduct. Given a situation the list of elements need not be exhaustive, one only needs to capture the essence of the situation. Once the strategic level elements are identified one can go down the levels identifying constituents at the lower levels. This process needs to be continued until one reaches a level where the elements are simple enough to be amenable to modelling by the available tools. The *In-MODE modelling and software architecture* [Davies et.al.(2002)] provides an excellent example of such a process for an Integrated Air Defence System. One can adopt this as a guiding framework to elicit the basic elements of both military and non-military components of any pol-mil-sec system.

In this report I *assume* that the adversary pol-mil-sec system of interest has already been identified, and its basic elements elicited, through previous analysis. In fact such analyses are beyond the scope of this work. Our sole aim, as has been stressed earlier, is to develop tools for EBO related analysis – more precisely to show how simulations through cellular automata could be used to investigate effects-based strategies once the basic elements are given. With this caveat in place let us now turn to a specific scenario for simulations.
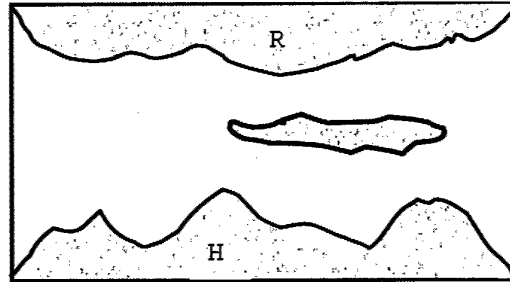
3.2.1 A Scenario for Simulation

Figure 3-5: A scenario that involves two opposing sides H ⧸and ⧸R where H is viewed as the friendly side while R constitutes the adversary along with a third independent small island nation lying in the sea gap between H and R.

Consider a scenario that involves two opposing sides H ⧸and ⧸R where H is viewed as the friendly side while R constitutes the adversary along with a third independent small island nation lying in the sea gap between H and R. The R forces have exploited the weakness of the independent country and have occupied it. There has been some international criticism, but the R leadership has claimed that the occupation was at the invitation of the legislative council of the independent nation. The H forces are strongly opposed to the occupation. The R leadership fears that the H forces plan to dislodge it from the occupied territory. They have embarked on a series of raids across the sea gap into H's territory as disruptive and diversionary actions. The R forces believe that the H forces will be unable to respond effectively to widespread raiding and will need to divert its attention from its opposition to the R force's occupation of the independent nation.

The H force's Military Strategic Objectives are:
1. Undermine R's leadership and
2. Neutralise R force's capacity to conduct or sustain offensive military operations against H's territory.

Traditional military operations planning require identifying the R *centre of gravity* (COG) [Falzon 2004] so that a course of action can be planned to undermine it. An analysis of the above scenario has been conducted by Falzon and Priest [2003] who identify the COG as

> *The will and ability (WA) of R to occupy the island nation and conduct offensive operations against H's territory.*

The analysis then goes on to identify the microscopic military elements, which must be interdicted to affect the COG.

3.2.2 The Parameters for Simulation

Let us now construct an automaton to simulate *strategies* that would undermine the COG, or in the case of our scenario, the *WA* of the R side. The basic elements identified in the COG study [Falzon and Priest 2003] would largely provide the basic military elements of the R side. To this we need to add the elements pertaining to the political and the socio-economic factors to complete the holistic picture. As mentioned before we expect these to be available through other similar studies. All these elements taken together will populate the cells in our automata. The question that arises now is - to what degree of detail must these basic elements be specified. Obviously more in-depth knowledge will enable more realistic simulation. However, our main aim here is to understand the patterns of global behaviour, the patterns of cascading effects, and not so much to understand the idiosyncrasies of a particular adversary composition. It turns out, most fortunately, that a lot can be gleaned about such patterns with surprisingly few details. Let me therefore explicate these necessary details.

Basic Structure of the Automaton:

I consider an $n \times n$ cellular automaton with cells representing various types of elements. Neighbouring elements in this automaton are not necessarily elements that are physically situated in close proximity. Rather, an element has as its neighbours all those elements, which have direct impact on its *WA value*. This means that we have to position the elements in the automaton in a manner that satisfies this dictum. This would however require a very detailed knowledge of the system being modelled, which is not feasible. As we shall see such exact positioning of the elements is not essential. I therefore sprinkle the elements in a random manner over the automaton keeping in mind the proportion $p : m : s$ of the political military and socio-economic elements of the R side respectively in our pol-mil-sec system. This proportion can be reasonably determined by counting the number of various elements in a representative sample of the system about which intelligence data can be gathered. The numbers p, m, s and n serve as parameters for the simulation and are fixed for the present set of simulations at

$n = 35$ and

$p : m : s :: 25 : 50 : 25$.

Furthermore I assume a *von Neumann* neighbourhood configuration. This implies that, for each element the automaton takes into account its interactions with only four other elements and neglects the rest.

The WA Values

R's *will and ability (WA)* will depend upon the *WA* of each of the elements or cells in our automaton. Let us denote the *WA* of a cell *C* at time *t* by the symbol $C_{wa}(t)$. We assess this in the scale $0 \leq C_{wa}(t) \leq 100$. The *WA* of a cell would naturally determine the state of the cell. A cell in the automaton can, however, have a finite number of states only. We therefore make the following discretization to obtain three distinct states:

Let $0 < b_1 < b_2 < 100$

If $0 \leq C_{wa}(t) \leq b_1$ we say that the state of the cell is *severely degraded*.

If $b_1 < C_{wa}(t) \leq b_2$ we say that the state of the cell is *degraded*.

If $b_2 < C_{wa}(t) \leq 100$ we say that the state of the cell is *fully effective*.
The numbers b_1 and b_2 provide two more parameters. In our simulations
$b_1 = 40$ and $b_2 = 75$
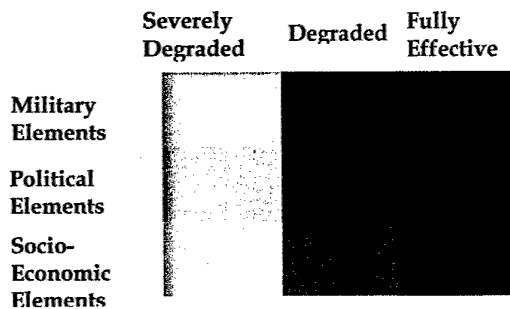and the states are represented through the following colour scheme.

Figure 3-6: Colour scheme representing the states of cells in the automaton.

Furthermore, we need to assign a *WA* value to each cell to initialise the simulation. The method adopted here is to assign these values randomly but satisfying a given statistical distribution. This particular distribution is determined from intelligence data – i.e. one considers a representative sample of the system regarding which intelligence data can be obtained, determines the *WA* value of each of the elements in this sample and then fits a statistical distribution to this collection of *WA* values.

How would one determine the *WA* value of an element? This is a problematic question. Clearly the *WA* value determines some kind of a *measure of effectiveness* and hence any attempt to find it will be fraught with the well documented difficulties that hinder similar efforts to determine the latter measure. It is not my intention to delve into these problems here. In practice, given a scenario, one determines various *measures of effectiveness* through procedures whose validity rests upon the nature of the scenario and the investigator's personal expertise and

knowledge. I assume some such semi-subjective procedure has been devised to determine the *WA* values.

In the following simulations the initial *WA* values satisfy a *Skew Distribution:*

The *WA* values are distributed in some sort of a bell shaped distribution about a certain modal value. I consider those that are *negatively skewed* with a *long tail* to the left of the *mode* and a *short tail* to its right as in Figure 3-7. This has the following interpretation:

a.   A significant number of cells have *WA* values clustered round the *mode*

b.   Cells having *WA* values higher than the mode give rise to a *short tailed* spread, right of the mode.

c.   Cells having *WA* values lower than the mode give rise to a *long tailed* spread, left of the mode.

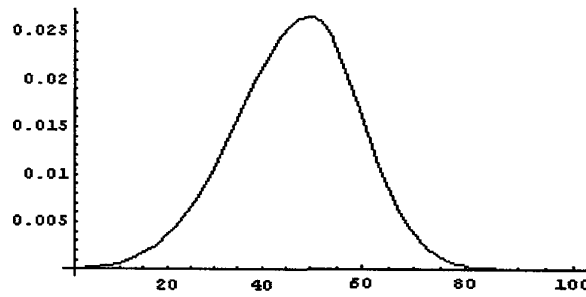I consider specific instances of these initial distributions below.

Figure 3-7: A Skew Distribution density function with a short-tailed spread to the right of the mode and a long-tailed spread to the left.

The State Updating Rule

To implement time evolution we have to specify the functional form of τ in Eq 3.1. This function determines how a cell interacts with its neighbours and updates its state. I adopt the following rule

$$C_{wa}(t+1) = \frac{\omega_{(C,C)}C_{wa}(t) + \omega_{(C,E)}E_{wa}(t) + \omega_{(C,N)}N_{wa}(t) + \omega_{(C,W)}W_{wa}(t) + \omega_{(C,S)}S_{wa}(t)}{\omega_{(C,C)} + \omega_{(C,E)} + \omega_{(C,N)} + \omega_{(C,W)} + \omega_{(C,S)}} \quad (3.2)$$

This is an *averaging rule.* It encapsulates a rather familiar tenet - if a strong element interacts with a weak one then over a period of time the strong element will have its efficiency reduced while that of the weak element will get boosted. The exact form of the averaging is captured by the coefficients $\omega_{(C,C)}$, $\omega_{(C,E)}$, $\omega_{(C,N)}$, $\omega_{(C,W)}$, and $\omega_{(C,S)}$.

Here $\omega_{(C,C)}$ weighs the inertia of the element *C* – a strong element will try to maintain its efficiency in an interaction while weak ones will have difficulty in lifting theirs. $\omega_{(C,C)}$, is another parameter for the simulation.

The rest of the coefficients weigh the influence on the element C imparted by its neighbours. This can be different for different elements. For example if C were a socio-economic element, it will be affected more strongly by a political rather than military element in its neighbourhood. The following nine parameters in the simulation determine these coefficients:

$$\omega_{(mil, mil)}, \qquad \omega_{(mil, pol)}, \qquad \omega_{(mil, sec)};$$

$$\omega_{(pol, pol)}, \qquad \omega_{(pol, mil)}, \qquad \omega_{(pol, sec)};$$

$$\omega_{(sec, sec)}, \qquad \omega_{(sec, pol)}, \qquad \omega_{(sec, mil)}.$$

Here for example $\omega_{(C,E)}$ will be given by $\omega_{(mil, pol)}$ if C were a military element and its neighbour E were political.

Again I assume that some semi-subjective procedure has been devised by domain experts to extract the coefficients from the available intelligence data. Because of the nature of Equation (3.2) all these coefficients are determined only up to a constant multiplicative factor. Keeping this in mind the following values are specified to run the simulations below:

$$\omega_{(C,C)} = 3;$$

$$\omega_{(mil, mil)} = 2, \qquad \omega_{(mil, pol)} = 1.5, \quad \omega_{(mil, sec)} = 1;$$

$$\omega_{(pol, pol)} = 2, \qquad \omega_{(pol, mil)} = 1, \qquad \omega_{(pol, sec)} = 1.5;$$

$$\omega_{(sec, sec)} = 2, \qquad \omega_{(sec, pol)} = 1.5, \quad \omega_{(sec, mil)} = 1.$$

3.2.3 Preliminary Simulations

Two aspects of the parameter specifications, or initial conditions, as detailed above need to be clarified before we proceed further. The first point deals with the positioning of the elements in the automaton. We have only determined the ratio of the elements and have then sprinkled the elements randomly over the automaton complying with that ratio, thus neglecting to capture the detailed nature of neighbourhoods. The second point deals with the initial distribution of WA values. As with the first point we have only determined the statistical distribution of the WA values and have then sprinkled the WA values randomly over the elements satisfying the determined distribution. The reason for not being any more specific is the vast amount of data one would need to fill in the details. However, as indicated earlier we do not need to get mired in the details because, we are only interested in understanding the patterns of global behaviour, and not in the idiosyncrasies of any particular set of initial conditions. All we need to do is run a large number of simulations starting from different realisations of the initial conditions and observe the statistical nature of the evolution and the patterns contained in it.

Figures 3-8, 3-9 and 3-10, show three instances of repeating the same simulation a large number of times. In each run the simulation satisfies the initial parameters specified in the section before. As per the points in question:

1. $p:m:s :: 25:50:25$ in each run, but the positioning of the elements are different and
2. the *WA* values are sprinkled randomly again in a different manner in each run though satisfying the following distribution each time.
   a. Mode of the distribution = 80
   b. A *short tailed* spread of cells with higher *WA* values given by the *right variance* = 10
   c. A *long tailed* spread of cells with lower *WA* values given by the *left variance* = 15
   d. 50% of *WA* values lie at or above the mode.

What we observe is that no matter how varied the initial configurations are, the final distributions of WA values have very similar patterns at the conclusion of each run[4]. This is the handiwork of the *averaging rule* (Equation (3.2)). As we shall see in the next section, final configurations would be quite different when the *averaging rule* is dominated by other rules guiding the evolution. The statistical nature of the initial configuration would then become important. Leaving that aside for future considerations, observe for now the different evolutions of the average *WA* values (Part F of each figure) in different instances of the simulation, indicating the different paths that the evolution traverses all of which nonetheless lead to similar final configurations.

---

[4] Experiments with other initial distributions e.g.
- distributions where the initial *WA* values are distributed normally with some *mean* and *variance*;
- distributions where they are distributed uniformly over a certain sub-interval [*a, b*] of the interval [0, 100] and;
- distributions where they are distributed over a number of disjoint sub-intervals [*a, b*], [*c, d*], [*e, f*], ..., of the interval [0, 100], each sub-interval containing a certain proportion of *WA* values which are distributed uniformly in that sub-interval;

all lead to the same conclusion.

Figure Captions

Part A of each figure depicts the initial configuration of the automaton according to the colour scheme prescribed in Section 3.2.2. These initial configurations, as can be seen clearly, are different in each run.

Part B of each figure plots the *WA* values of the initial configuration. The horizontal axis represents the individual cells numbered from 1 to 1225 (35×35). The numbering starts with the cell at the upper left hand corner having number 1, increases along each row from left to right, and ends with the cell at the lower right hand corner having number 1225. The vertical axis denotes the initial *WA* values assigned to the cells. These values are assigned randomly in a different manner in each of the run.

*Part C* of each figure depicts the final configuration after 2000 time steps.

Part D plots the final *WA* values after 2000 time steps. Similar patterns are seen at the conclusion of each run.

Part E of each figure plots the number of elements in different states as time develops. The horizontal axis represents time steps from 1 to 200 and the different coloured plots count elements in different states as follows:

▬▬▬▬▬	counts the number of *fully effective* elements at any time step,
▬ ─ ─ ─ ─ ─ ┐	counts the number of *degraded* elements at any time step and
▬▬▬▬▬	counts the number of *severely degraded* elements at any time step.

It is clear that with the above initial condition all the elements reach the *fully effective* state before the 50th time step in each run.
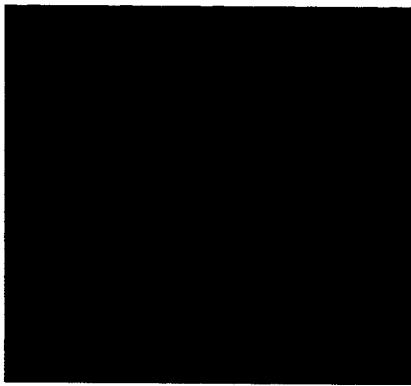
Part F of each figure plots the average *WA* value. The horizontal axis plots time steps while the vertical axis represents the *WA* value at any time step averaged over all the cells in the automaton. After a period of initial fluctuations the average value settles down to a value around 77.7 in each run.
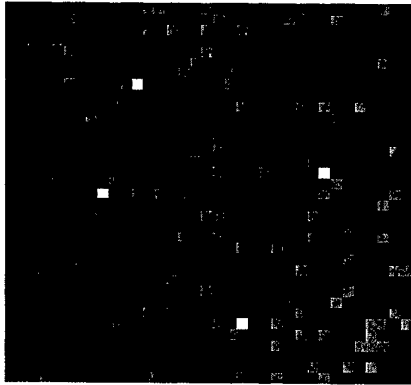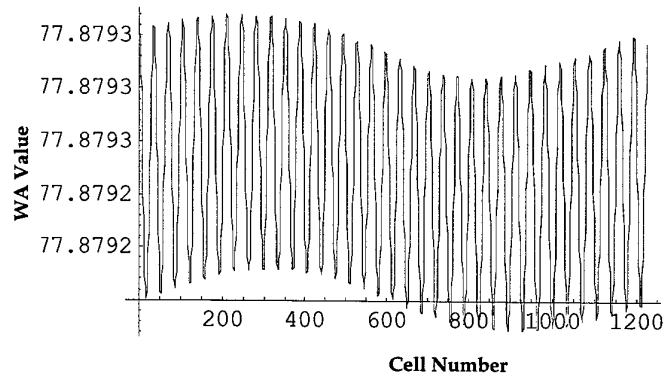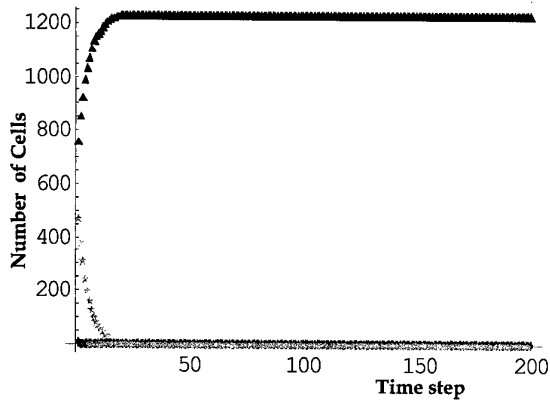
(A)
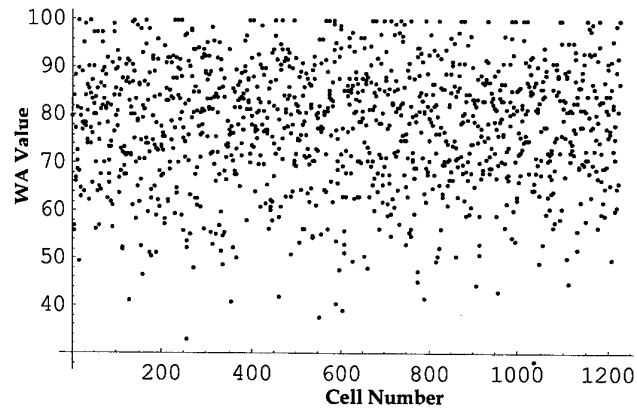
(B)

(C)

(D)

(E)

(F)

Figure 3-8: Results of one instance of simulation. (A) and (B) show initial configuration, while (C) and (D) show final configuration after 2,000 steps of evolution. (E) depicts the evolution of the number of cells that are either fully effective or degraded or severely degraded and (F) plots the average WA value (See the Figure Captions on Page 16 for details).
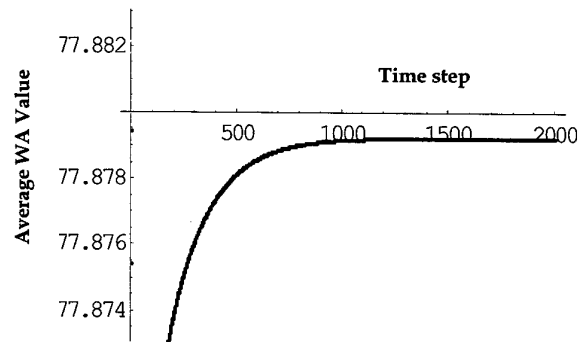
(A)

(B)

(C)

(D)

(E)

(F)
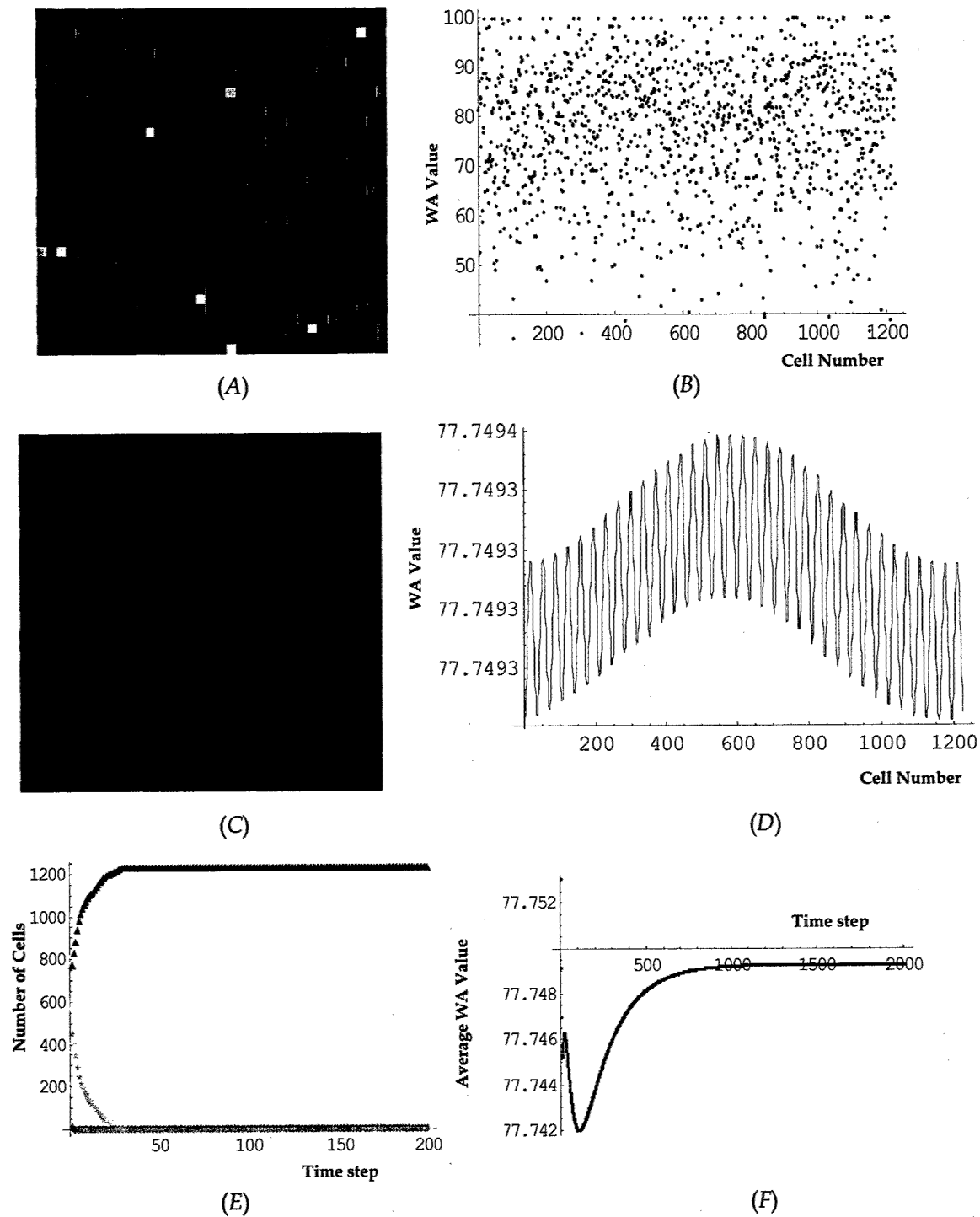
Figure 3-9: Results of a second instance of simulation. (A) and (B) show initial configuration, while (C) and (D) show final configuration after 2,000 steps of evolution. (E) depicts the evolution of the number of cells that are either fully effective or degraded or severely degraded and (F) plots the average WA value (See the Figure Captions on Page 16 for details).

(A)

(B)

(C)

(D)

(E)

(F)

Figure 3-10: Results of a third instance of simulation. (A) and (B) show initial configuration, while (C) and (D) show final configuration after 2,000 steps of evolution. (E) depicts the evolution of the number of cells that are either fully effective or degraded or severely degraded and (F) plots the average WA value(See the Figure Captions on Page 16 for details).
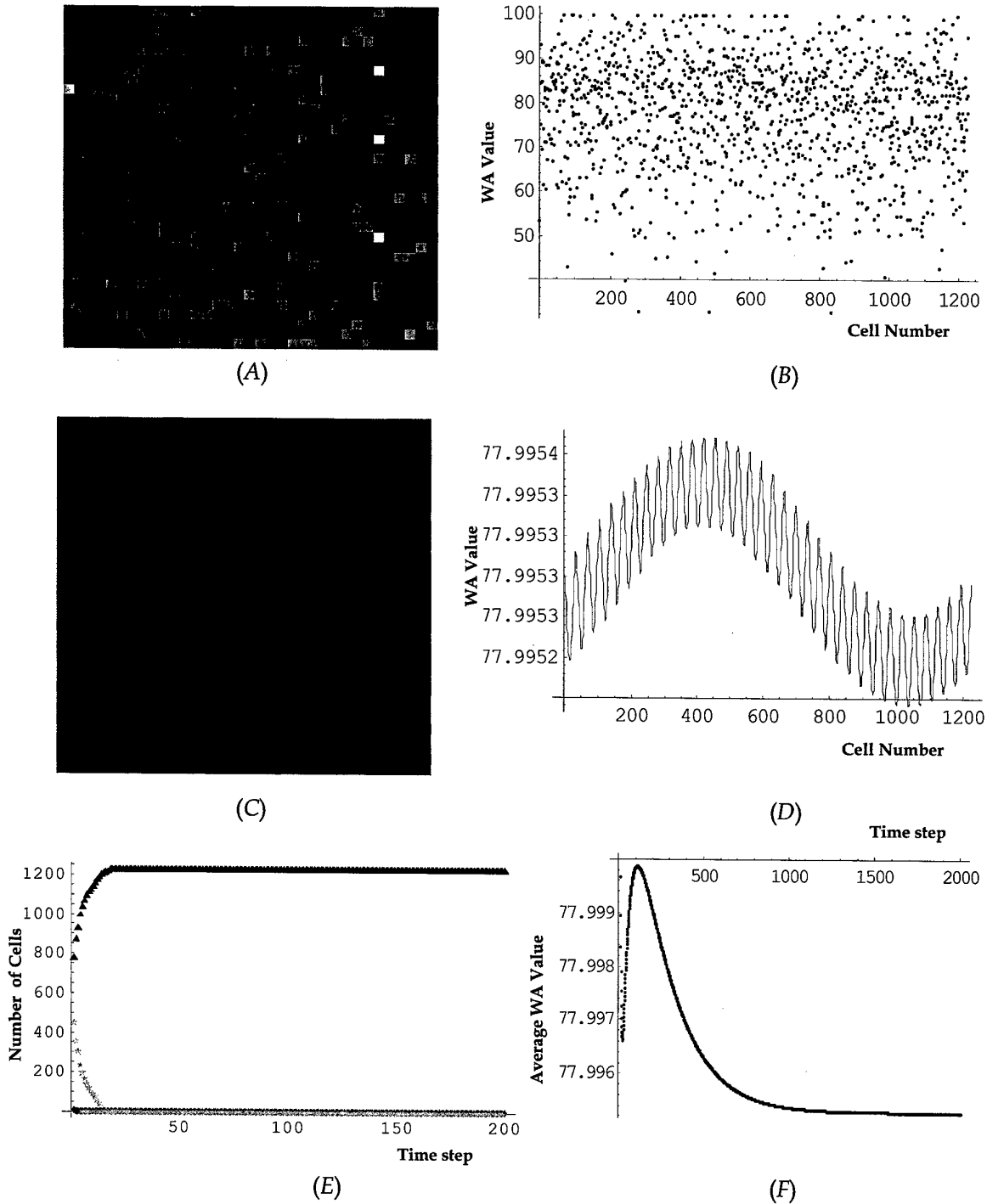
3.2.4 Simulating Interdiction

The aim of any interdiction is to reduce the *WA* values of the R elements. Interdiction can be modelled by altering the initial *WA* value distribution in any combination of the following:

- Shift the *mode* to the left - to lower values.
- Decrease the *right variance*, i.e. decrease the spread at *WA* values higher than the mode.
- Increase the *left variance*, i.e. increase the spread at *WA* values lower than the mode.
- Increase the percentage of *WA* values left of the *mode*.

In Figure 3.11 we show an instance of running the simulation with interdiction applied to the initial distribution of *WA* values as specified in Section 3.2.3. The interdiction is manifest in the following alterations:

a. Mode of the distribution shifted left to the value 78
b. *Right variance* = 10
c. *Left* variance = 20
d. 55% of *WA* values lie at or below the mode

As can be seen in the diagram 3.11(E), all the elements attain the *degraded* state before the 50th time step as opposed to the original evolutions where they had all gained the *fully effective state* by this time step. This is true for every run where the above interdiction has been applied to different realisations of the initial conditions as discussed in Section 3.2.3.

I have used Section 3 to lay down the basic parameters that govern our simulations. The results described here are only significant as far as the process of explaining these basic parameters go. There is, in fact, a major shortcoming in the way I have modelled interdiction to adversary forces. All the interdictions are applied to the initial conditions and the automaton is allowed to run from the interdicted initial conditions without any further disturbances. In practice, however, the H side will interdict the R side continually as time develops and the R side will react to this interdiction. I take up these and related questions leading to more interesting simulations in the following section.
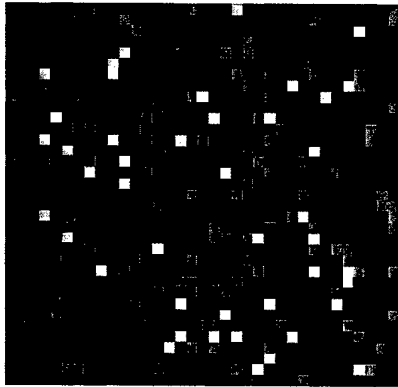
(A)
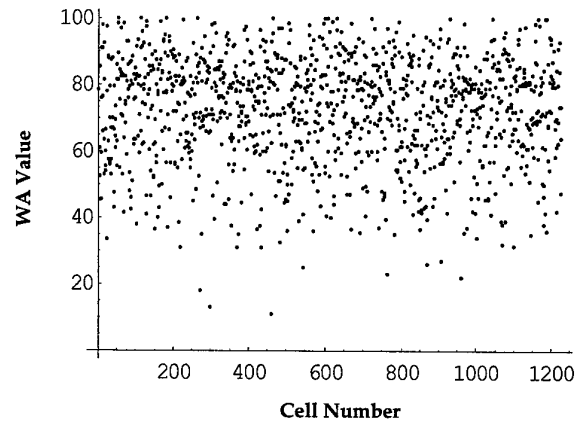
(B)
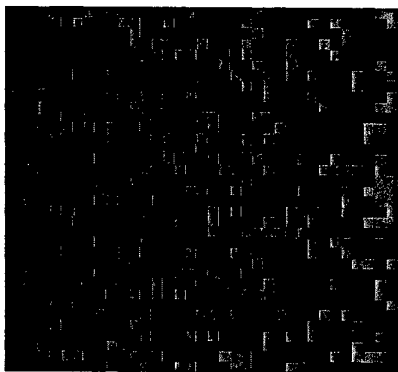
(C)

(D)

(E)

(F)

Figure 3-11: Results of an instance of simulation with interdiction. (A) and (B) show initial configuration, while (C) and (D) show final configuration after 2,000 steps of evolution. (E) depicts the evolution of the number of cells that are either fully effective or degraded or severely degraded and (F) plots the average WA value (See Figure Captions on Page 16).
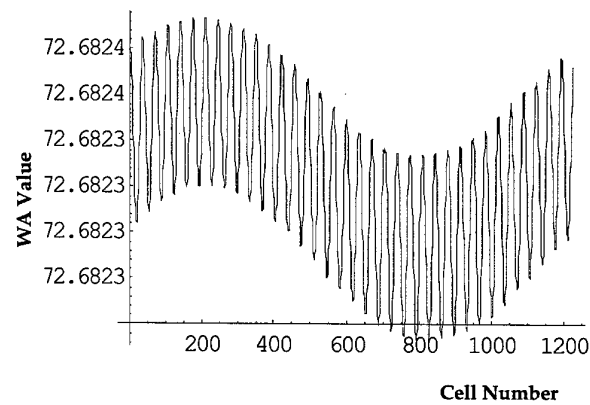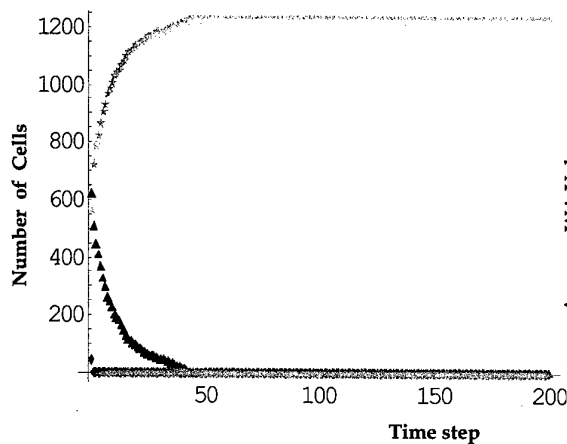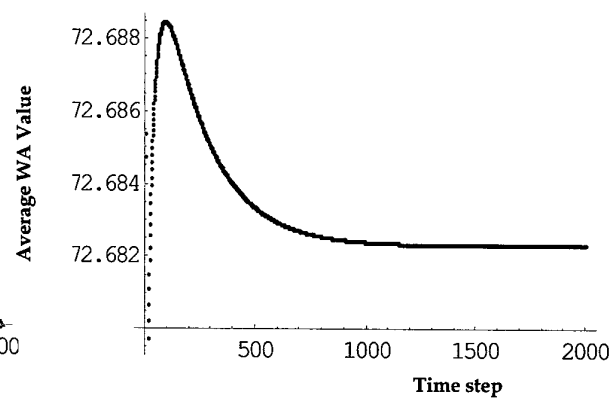
4. An Effects-Based Strategy

This section puts forward a basic strategy to implement effects-based operations. I will motivate the discussion by elaborating the strategy in terms of our adopted scenario described Section 3.2.1. From an EBO point of view it can be argued that although the goal is still to undermine the *will and ability* of the adversary, achieving this goal through the use of full scale military force projection can be counter productive. This will most probably provide grounds for the escalation of the conflict. The leadership controlling the R forces will be quick to exploit the H force's responses to paint the situation as a serious threat to their national sovereignty and commit to the conflict on a much larger scale. This in turn would enable the R leadership to strengthen its popular support – a state of affairs not conducive to H 's strategic goals.

I will argue that instead of seeking a purely militaristic solution one should respond to the adversary action on all fronts using military, diplomatic and economic means. Instead of imparting large military disturbances to the adversary one should impart a large number of small disturbances to the adversary's military, political and socio-economic establishments. These disturbances can be given randomly, in an opportunistic manner, and would produce random and minor first order effects which may go unnoticed by the R leadership. However the higher order effects of these small disturbances will eventually add up to produce large-scale cascading avalanches in an unpredictable fashion. This will catch the R leadership unawares and will most probably be interpreted by the general populace as its inability to cope with the situation, severely undermining its authority. The R leadership would then have to divert its attention from incursion into H 's territory to contain the situation at home.

The question before us now is the following. *Will small disturbances eventually add up to produce large-scale cascading avalanches in an unpredictable fashion?* The answer is 'yes' – and this is what I am going to demonstrate through simulations with cellular automata. Before doing that, however, let me clarify the basic principles governing this strategy.

Although the above strategy is spelled out with respect to the particular scenario chosen, any *effects-based strategy* would differ only in the details while incorporating the same underlying basic principles. More specifically, I stipulate that a strategy will be called an *effects-based strategy* if it satisfies the two necessary criteria that underpin an *effects-based operation*– the strategy should be *holistic* and should aim at *exploiting higher order effects*.

> *Holistic*: An effects-based strategy should impart interdictions to the adversary on the entire pol-mil-sec spectrum. This requires an integrated national effort that seamlessly blends all national capabilities - political, military and socio-economic.

The justifications for such an integrated strategy have been discussed widely in the literature [Forestier (2001), Saunders-Newton & Frank, (2002)].

Exploiting immediate and higher order effects: Instead of planning for overwhelming large-scale interdiction, the strategy should be to impart a large number of relatively small disturbances across the pol-mil-sec spectrum, creating just enough instability in each instance but whose cumulative effects would drive the adversary towards a state compatible with the friendly forces strategic aims. These small-scale interdictions would be diverse and semi-autonomous and be directed predominantly at the targets of opportunity presented by the adversary forces. Additional advantages of such small-scale interdictions are that they make the strategy dynamic and adaptive.

How can we achieve integrated national capabilities is a matter for further investigation, and not of immediate relevance to our analysis. Let us therefore assume that the H side has achieved a minimum amount of integration for spectrum wide interdiction. However, how to formulate a strategy that would exploit higher order effects is a question of central importance to our analysis and would occupy our attention for the rest of this report.

Ideally one would plan the above mentioned small-scale operations to exploit the opportunities provided by the adversary. This, however, would require a detailed knowledge of the state of the adversary forces. Since this is rather hard to obtain, let us assume that opportunities arise randomly across the adversary elements. Accordingly we select adversary elements at random to impart interdiction. The next question is what would be the magnitude of any of these interdictions? Again this will require a detailed knowledge of the particular element chosen for interdiction, as that would not be easily available, we assume that all interdictions are set at a predetermined magnitude. These are of course standard assumptions, tacitly made prior to the kind of statistical study we plan to undertake. *However, the point I want to establish here is this - if we can show that random operations which inflict a certain minimum amount of interdiction to the adversary at each instance, would give rise to higher order effects which would combine to form large-scale debilitating avalanches, then any other operation which is better informed will do the job even better.*

The above is again a reminder stressing the need for in-depth intelligence for the conduct of efficient EBO. The discussions below formulate a *minimal strategy for interdiction* based on the above premises.

Remark: Superficially it would appear that the adopted strategy discounts all large-scale interdictions. This is not so if the large-scale interdiction can be represented as the sum of a large number of small-scale interdictions. If it is possible to model the large-scale interdiction as a series of small-scale interdictions $I_1, I_2, ..., I_n, ...,$ sequenced over the epochs $t_1, t_2, ..., t_n, ...,$ respectively. In this case the higher order effects of earlier interdictions will add up with the lower order effects of later interdictions to produce the cumulative effects we are interested in our simulations.

4.1 Formulation of a Minimal Strategy for Interdiction

In Section 3 we constructed an automaton to simulate the evolution of our adopted scenario. We observed how the automaton evolved from specified initial conditions updating its state at each time step according to the *averaging rule* specified in Eq 3.2. We then studied a preliminary version by applying interdiction to the initial conditions and allowing the automaton to evolve without any further disturbances. In real situations the evolution will be more involved, being influenced by a number of competing factors. At least one has to take into account the facts that H 's interdiction would not just be confined to one initial instance and that R would endeavour to undo the damage inflicted by H whenever it can. In the least therefore a realistic simulation should be able to handle a mode of evolution dictated by the following three factors:

A. The H side *interdicts* the elements of the R side continually as time develops.

B. The R side reacts to the interdictions trying to restore the affected elements.

(This is essentially what the *averaging rule* does. This rule can be interpreted informally to mean that when an element is interdicted its neighbours get together to restore its effectiveness to an extent that is possible given their own levels of effectiveness.)

C. Some R elements also increase their effectiveness spontaneously through *creativity and ingenuity* as the situation develops.

The stability and effectiveness of the R pol-mil-sec system will depend upon the interplay between H 's *interdiction* and R 's *creativity* superimposed on the evolution with the *averaging* rule. We have already implemented the *averaging* rule in our simulations in Section 3. Let us now go on to show how H 's *interdiction* and R 's *creativity* can also be implemented.

R 's *Creativity*:

As time proceeds some R elements may increase their *WA* values spontaneously. I implement this boost through *creativity*, in the following manner. Consider an element C whose *WA* value at time step t is given by $C_{wa}(t)$. If C has a boost to its *WA* value at this time step, then at the next time step its *WA* value is given by:

$$C_{wa}(t+1) = C_{wa}(t) + \lambda[100 - C_{wa}(t)], \quad 0 < \lambda < 1. \qquad (4.1)$$

The extent of increase to the *WA* value through *creativity* is directly proportional to the factor λ. For a given λ, the boost is higher for lower *WA* values and lower for higher *WA* values.

The next step is to specify the number of creative elements $g(t)$, at any time step t, that would spontaneously boost their *WA* value. This is given as

$$g(t) = \text{Nearest integer to } |u(t)|$$

where $\{u(t_1),\ u(t_2),\ \dots\ ,\ u(t_n),\ \dots\}$ is a set of numbers, one for each time step t_n, generated randomly, with the criterion that the collection of these numbers obey a normal distribution with mean 0 and variance σ.

In the absence of any prior knowledge I assume that every element in the R pol-mil-sec system is equally likely to be a candidate for *creativity* at any time step. Accordingly at any time step t, $g(t)$ number of elements are selected at random, from the set of all elements, for boost to their *WA* values according to the prescription (4.1). The idea here is that at most time steps the number of elements chosen for boost will be a small number, often equal to zero. Once in a while though, a large number of elements will get chosen and the distribution of these small and large numbers is given by the variance σ.

The parameters λ and σ govern the evolution of R's *creativity*. They are to be determined subjectively by the domain expert from his appreciation of the R side culture. This is yet another instance, which drives home the fact that an effects-based strategy requires a deep understanding of the adversary culture for its implementation.

H's Interdiction:

H's *interdiction* will be applied continually as time develops and as argued before I propose to implement a *minimal strategy for interdiction* in the following manner. If the element C has been interdicted at the time step t, its *WA* value at the next time is given as:

$$C_{wa}(t+1) = (1-\mu)C_{wa}(t),\ 0 < \mu < 1. \tag{4.2}$$

The extent of interdiction is directly proportional to the factor μ.

The number of elements $h(t)$, chosen for interdiction at any time step t, is given by

$$h(t) = \text{Nearest integer to } |v(t)|$$

where $\{v(t_1),\ v(t_2),\ \dots\ ,\ v(t_n),\ \dots\}$ is a set of numbers generated randomly, with the criterion that the collection of these numbers obey a normal distribution with mean 0 and variance ρ. Hence at any time step t, I choose $h(t)$ number of elements randomly, from the set of all elements, to which interdiction is applied according to the rule (4.2).

The parameters μ and ρ determine the continual application of H's *interdiction*. To satisfy our stipulations for a strategy to be an effects-based strategy, one must ascertain that the magnitude of H's *interdiction* is just sufficient to tip the balance. It should not be too large to destabilise R beyond a certain threshold. Nor should it be too small so that R can ride over these disturbances using the processes of *averaging* and *creativity* and maintain a level of *WA* above the threshold. Again, if the magnitude of H's *interdiction* is very large then the first and second order effects will be big enough to destabilise the R forces severely. There would be no need to take the higher order

effects into account. *The power of EBO is well demonstrated in those balancing situations where the threshold is just crossed.*

The question that arises immediately is - what is this threshold and how does one determine it? The threshold, and what it signifies, has to be specified keeping in mind the desired strategic end state. To pave the way for a precise formulation let us consider the following specifications:

▶ We say that a *degrading (upgrading) avalanche* of magnitude M, with respect to the threshold *WA* value T_{WA}, has occurred in the time interval $[t, t+\Delta]$, if in this time interval the *WA* values of M elements in the R pol-mil-sec system have decreased (increased) from a value above (below) T_{WA} to a value below (above) it.

▶ The *steepness S* of the *avalanche* is given by M/Δ

▶ We now set H 's *strategic goal* as that for achieving a *degrading avalanche* of a certain magnitude $\overline{M}$ with respect to a certain threshold *WA* value $\overline{T_{WA}}$ having a certain steepness $\overline{S}$.

Remark: Avalanches are manifestations of higher order effects. When a degrading avalanche ensues, say at time step t, it means that the cumulative effects of all instances of H 's interdictions applied before this time step have finally overcome the cumulative effects of the *averaging* rule and that of R 's *creativity* to produce a downward trend in R 's *will and ability*. The threshold $\overline{T_{WA}}$ fixes a level such that when enough R elements, at least $\overline{M}$ of them, fall below the threshold in their *WA* values, the decline provides sufficient compelling reasons for R to abandon its hostile activity against H . Again, for R to abandon hostility the decline should be fast rather than gradual and this is where the *steepness* of the *avalanche* comes into play – a very steep *degrading avalanche* will appear like a sudden disaster occurring with no apparent discernible cause. Moreover, the magnitude of H 's *interdiction* should be just enough to create the right avalanche, while not driving the *WA* values of the R elements far below the specified threshold, as this would most probably trigger instability leading to effects not conducive to the desired strategic end state. This last point, as I have stressed upon before, is central to the EBO philosophy adopted here and sets it apart from the kind of philosophy that aims at annihilation and collapse of the adversary pol-mil-sec system.

A minimal strategy for interdiction is therefore one which produces, with an acceptable degree of probability, the least destructive degrading avalanche, that is strong enough to satisfy the set H 's strategic goal.

4.2 Simulations Investigating a Minimal Strategy

We now ask the following question - given a certain *averaging rule* and a certain mode of R *'s creativity* what should be the *minimal strategy for interdiction* by H such that the specified H *'s strategic goal* is achieved?

Let us fix the above question by specifying the parameters so that we can find the answer by conducting simulations:

I. As before I consider a 35×35 automaton with the elements distributed randomly in the ratio $p : m : s :: 25 : 50 : 25$.

II. The *WA* values are sprinkled, again randomly, while satisfying the following skew distribution.

1. Mode of the distribution = 65
2. A *short tailed* spread of cells with higher *WA* values given by the *right variance* = 15
3. A *long tailed* spread of cells with lower *WA* values given by the *left variance* = 25
4. 55% of *WA* values lie at or below the mode.

The automaton evolves obeying the same *averaging rule* as specified in Section 3.2.2. However unlike then the evolution is now punctuated with R *'s creativity* and H *'s interdiction.*

R *'s creativity* is specified by the parameters $\lambda = 0.5$ and $\sigma = 1.5$

For H *'s interdiction* one can vary both the parameters, ρ which determines how extensive the interdiction is at each step, and μ which determines its magnitude. Varying these one can obtain the appropriate level of interdiction. For the present let us fix ρ at 6.3 (for no special reason) and vary μ to accomplish H *'s strategic goal*, which is set as follows:

Achieve a *degrading avalanche* of magnitude $\overline{M} = 490$, (which is 40% of the total number of elements) with respect to the threshold *WA* value $\overline{T_{WA}} = 55$, and having a steepness $\overline{S} \geq 2.5$.

Simulations were carried out using the parameters specified above but with different values of μ. Each simulation ran for 10,000 time steps. The results show that for all values of $\mu \leq 0.09$, about 80% or more of the elements retained a level of *WA* value that is above the specified threshold at any point of time. Fig. 4-1 shows the result of one such simulation with $\mu = 0.09$. For $\mu \geq 0.1$ most of the cells dropped below the threshold in their *WA* values by the time step 2000 in almost all runs of the simulation. In other words, when interdictions failed to achieve at least 10% reduction in the *WA* values in each instance, the desired strategic effects were not achieved.
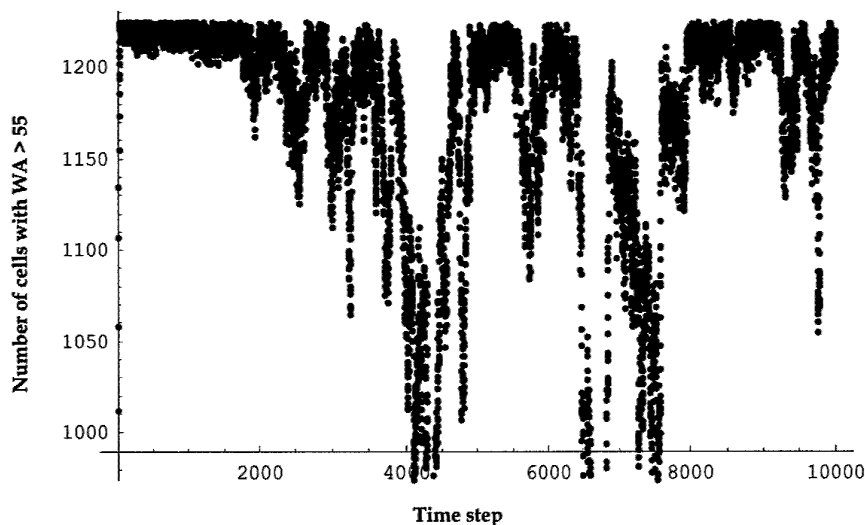
Figure 4-1: Results of a simulation with $\mu = 0.09$, 9% reduction in the WA values. The horizontal axis represents time steps. The vertical axis counts the number of elements that have their WA values above the threshold value of 55. The number of elements having WA values above the threshold never goes below 975.

For $\mu = 0.1$, H 's *strategic* goal was achieved in a number of simulations. Let us discuss this case in detail. Figures 4-3, 4-4 and 4-5 show three sample results chosen from a large collection of such results. These results were obtained by repeating the simulation over and over again, each instance being governed by the parameter values specified in this section and with $\mu = 0.1$. The three cases exhibit typical behaviours.

In Fig 4-3(E) almost all elements maintain a *WA* value above the threshold value of 55 until very near the time step 1500 when an avalanche ensues degrading nearly all the elements to a level below the threshold. In Fig 4-4(E) avalanches start much earlier and by the time step 1200 all but 100 elements have fallen below the threshold *WA* level. However a process of recovery starts around the time step 4000 which falters for a while but picks up momentum as time goes on. Most of the elements recover through an upgrading avalanche as shown by the peak around the time step 6500 only to encounter a subsequent steep avalanche which again degrades most elements. There is another attempt at recovery as late as the 10000th time step.

Whereas degradation of the *WA* values is a result of *interdiction,* recovery is fuelled by *creativity* on the part of the R elements. In Figure 4-5(E) we see multiple attempts at recovery with varying degrees of success. This characteristic of the simulations mean that the present interdiction strategy with $\rho = 6.3$ and $\mu = 0.1$ is not destabilising and does not overwhelm the R elements. This is also evident from the evolution of the average value as shown in part (F) of each figure. After an initial fall the average values oscillate about the value 54, occasionally rising above the threshold mark of 55, as would be expected from the recovery trends in the corresponding part (E) of the figure.

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This means that the interdiction strategy succeeds in inflicting an initial level of degradation in the elements as was intended, however, after a certain level of degradation the effects of *creativity* catch up holding back any further degradation.

Each simulation was run for 10,000 time steps, mainly to establish the trend that results from the interplay between H 's *interdiction* and R 's *creativity* superimposed on the evolution with the *averaging* rule. In many cases however, such a long run has little practical value. Our argument is that after a degrading avalanche satisfying the criteria set in H 's *strategic goal* has been achieved the R side would be compelled to abandon hostility, thus changing the situation altogether and requiring possibly very different responses from the H forces. Hence the time evolutions are of interest only up to the occurrence of the first such avalanche. The recoveries indicated in Figure 4-4(E) & Figure 4-5(E) will not happen if an earlier strong avalanche has compelled the R side to alter its course of action. Of course if R is willing to bide time and get across the low points then it would reap the benefits of future recovery. If this happens then the intensity of H 's *interdiction* has to be increased and the parameters in H 's *strategic goal* have to be reset for more debilitating avalanches.

Figure Captions

Part A of each figure depicts the initial configuration of the automaton according to the colour scheme prescribed in Figure 4-2. These initial configurations, as can be seen clearly, are different in each run.
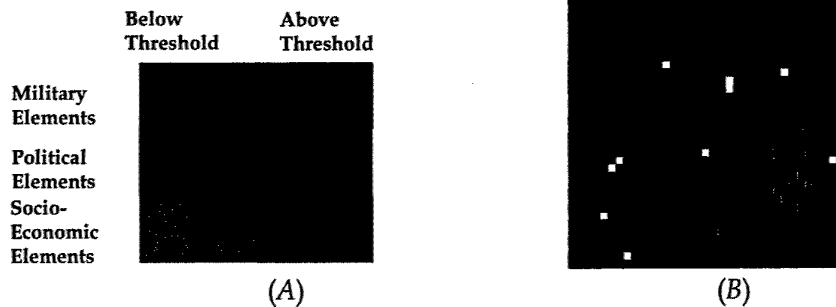

*Figure 4-2: (A) Colour scheme representing the states of cells in the automata displayed in subsequent figures. (B) An illustration of the colour scheme at a particular epoch during evolution. Cells which have been interdicted at that epoch, are coloured **yellow** while cells which have exhibited creativity at that epoch, are coloured **white**.*

Part B of each figure plots the *WA* values of the initial configuration. The horizontal axis represents the individual cells numbered from 1 to 1225 (35×35). This numbering has been explained in Section 3.2.3. The vertical axis denotes the initial *WA* values assigned to the cells.

*Part C* of each figure depicts the final configuration after 10000 time steps.

Part D plots the final *WA* values after 10000 time steps. . It is interesting to compare these with previous such plots, say the one shown in Figure 3.8*D*. The plot in Figure 3.8*D* is much smoother - it is a result of evolution with the *averaging* rule only, and this rule endeavours to smoothen the differences in the *WA* values of neighbouring cells. The plot in Figure 4-3*D*, on the other hand is a result of evolution with the *averaging* rule being continually disturbed by *interdiction* and *creativity*. The spikes are a result of these disturbances.

Part E of each figure plots time steps from 1 to 10000 along the horizontal axis while the vertical axis counts the number of elements that have their *WA* values above the threshold value of 55.
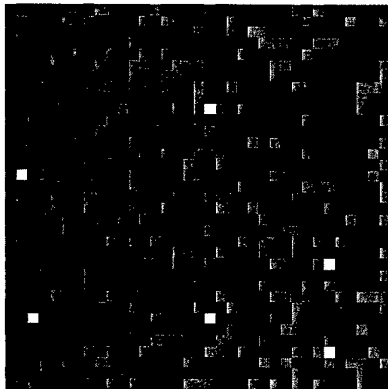
Part F of each figure plots the average *WA* value. The horizontal axis plots time steps while the vertical axis represents the *WA* value at any time step averaged over all the cells in the automaton.
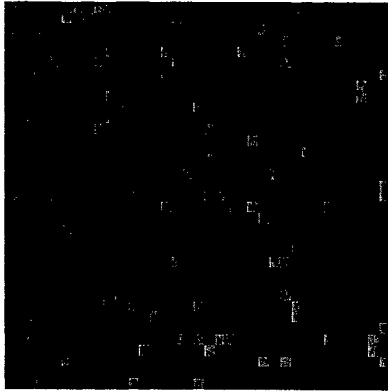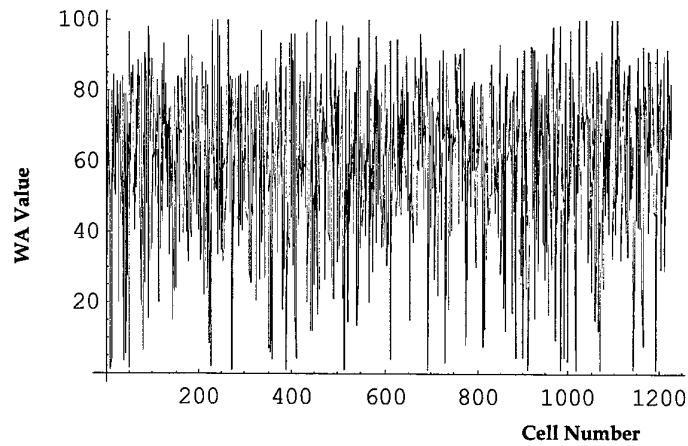
Figure 4-3: Results of one instance of simulation. (A) and (B) show initial configuration, while (C) and (D) show final configuration after 10,000 steps of evolution. (E) depicts the evolution of the number of cells that have WA values above the threshold value of 55 and (F) plots the average WA value (See the preceding text for details).
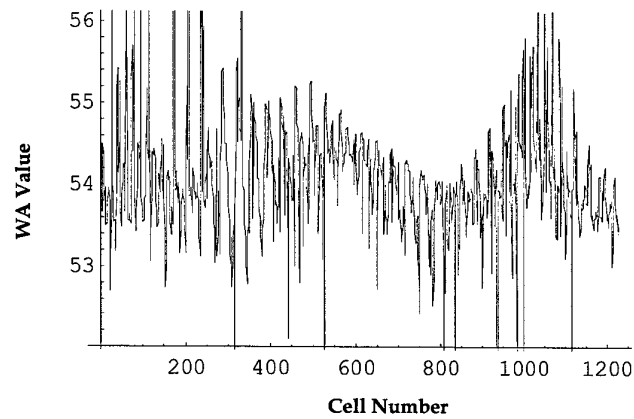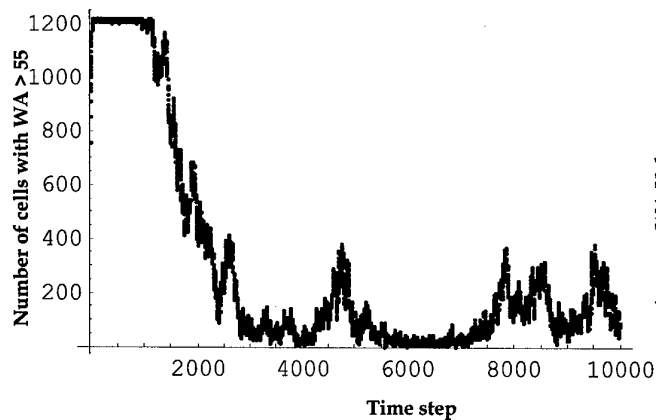
(A)

(B)

(C)

(D)

(E)

(F)
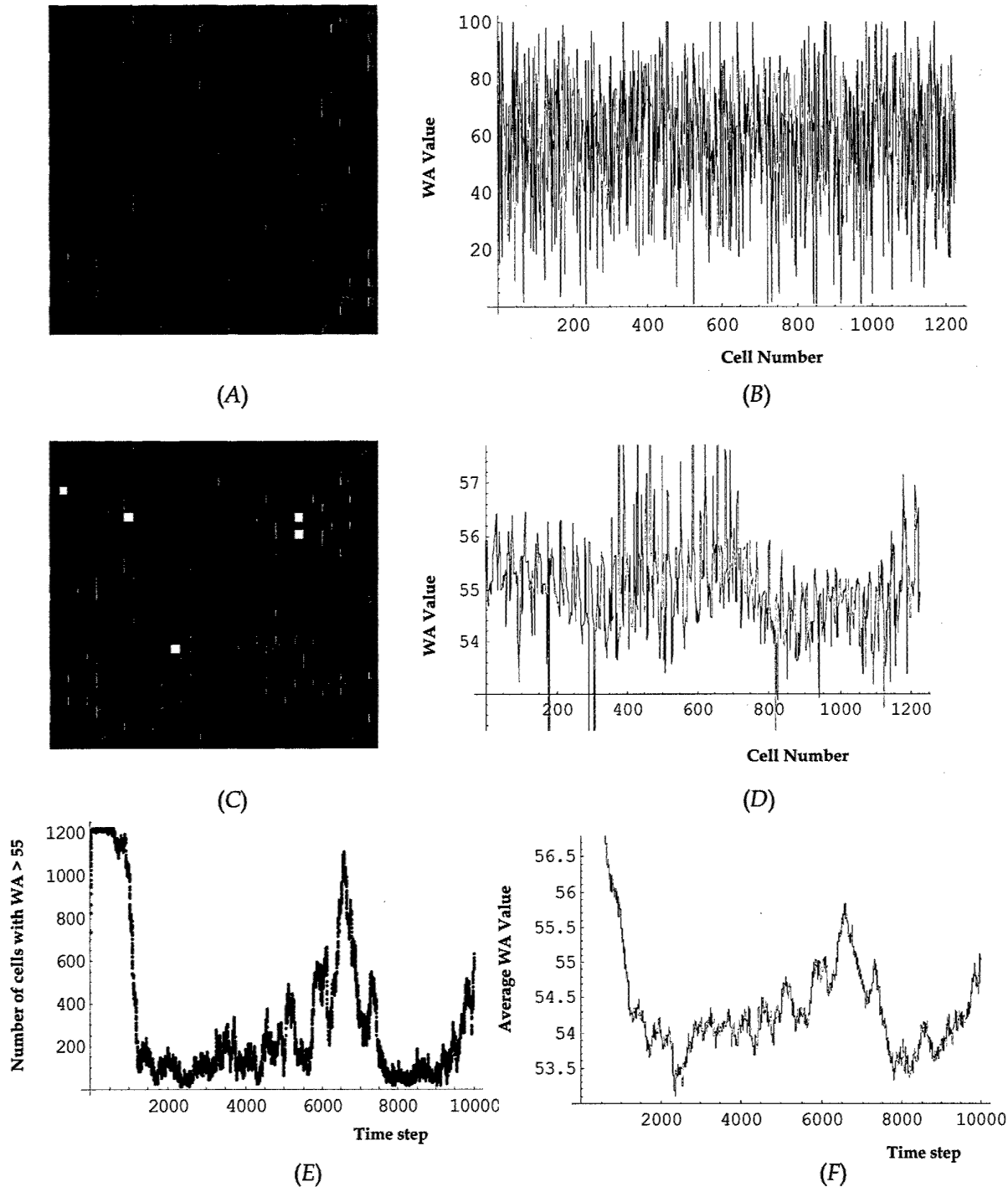
Figure 4-4: : Results of a second instance of simulation. (A) and (B) show initial configuration, while (C) and (D) show final configuration after 10,000 steps of evolution. (E) depicts the evolution of the number of cells that have WA values above the threshold value of 55 and (F) plots the average WA value (See the preceding text for details).
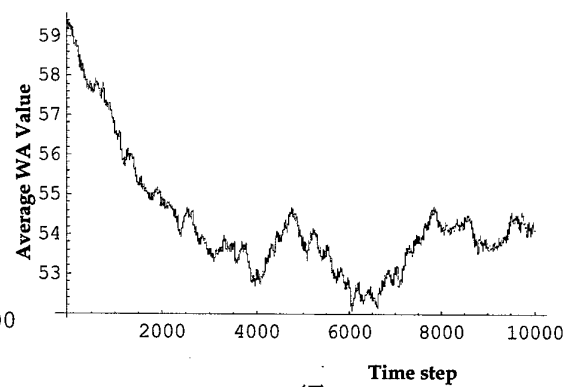
Figure 4-5: : Results of a third instance of simulation. (A) and (B) show initial configuration, while (C) and (D) show final configuration after 10,000 steps of evolution. (E) depicts the evolution of the number of cells that have WA values above the threshold value of 55 and (F) plots the average WA value (See the preceding text for details).
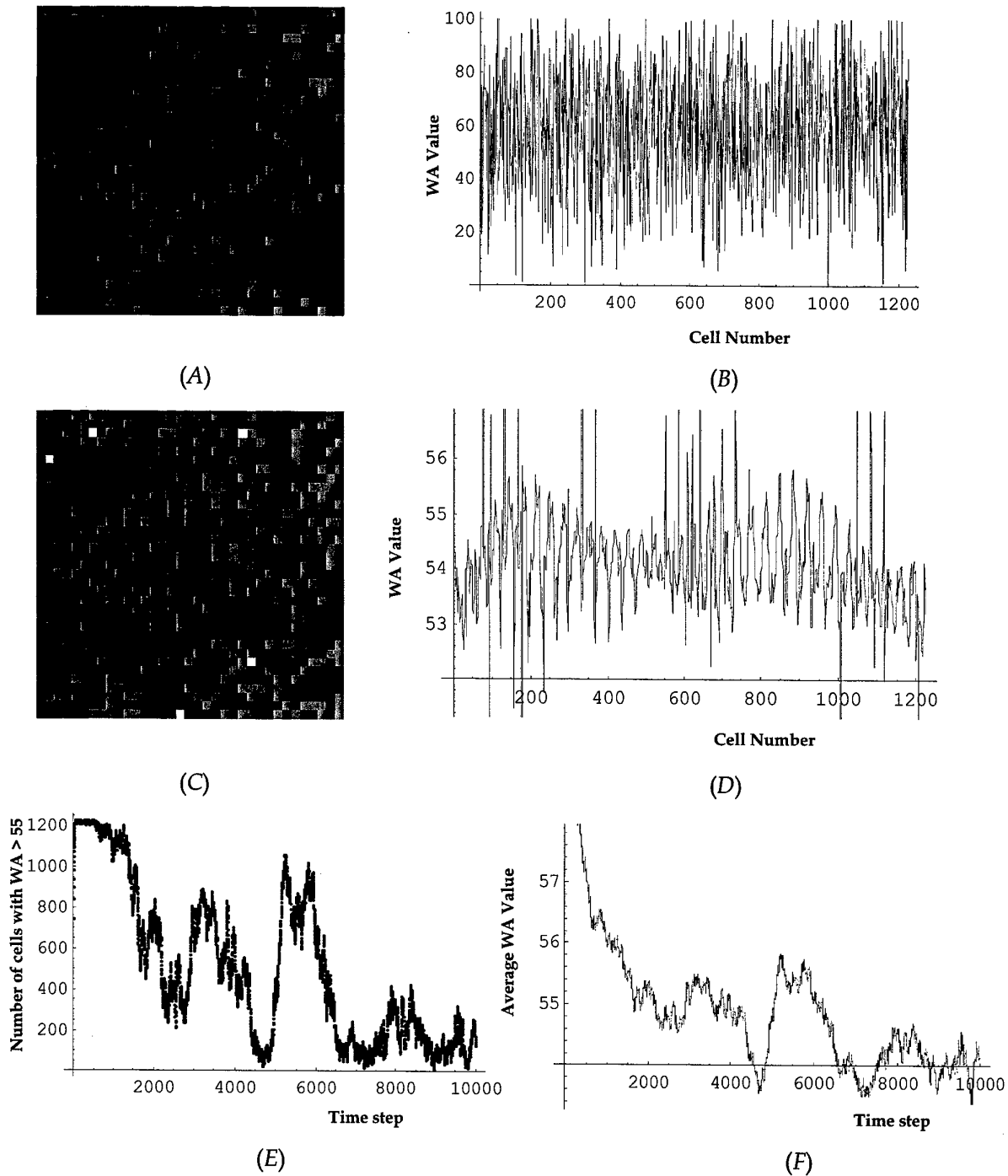
4.3 Analysis of Simulation Results

All simulations start with an upgrading avalanche and almost all the elements in the respective automaton achieve a WA value greater than the threshold value by the time step 50. This initial rise is the work of the *averaging* rule which dominates the evolution at the outset. Substantial degrading avalanches almost never occur before the time step 500. Recall that all the simulations start with the initial conditions I and II specified at the beginning of Section 4.2 and evolve according to the *averaging* rule given in Section 3.2.2, R*'s creativity* specified by $\sigma = 1.5$ and $\lambda = 0.5$, and H*'s interdiction* specified by $\rho = 6.3$ and $\mu = .1$. With these criteria the cumulative effects of *interdictions* start to dominate over the cumulative effects of *averaging* rule and *creativity* by the time step 1000 in almost all runs, and we observe major downgrading avalanches by this time step. As pointed out before the boost through *creativity* is stronger at lower *WA* values. Hence as *interdiction* drives the *WA* values of the elements down, it also inadvertently strengthens the boost through *creativity* until a *dynamic stability* is reached between these two effects at a certain level of the average *WA* value. *Interdiction* would not be able to drive the average *WA* value down any further and this average value starts to oscillate about a level characterising the stability. What our simulations show is that the adopted criteria provide the right dose of *interdiction* such that this dynamic stability is reached close to the threshold *WA* level specified by H*'s strategic goal*. To see this let us make a quantitative analysis of the simulations.

4.3.1 Computing Avalanche Strength

For the sake of concreteness let me start by discussing one run of the simulations with greater detail. In this instance I will concentrate on the variation in the number of elements that have their *WA* values above the threshold value of 55. Figure 4-6 depicts this variation for the chosen simulation run.
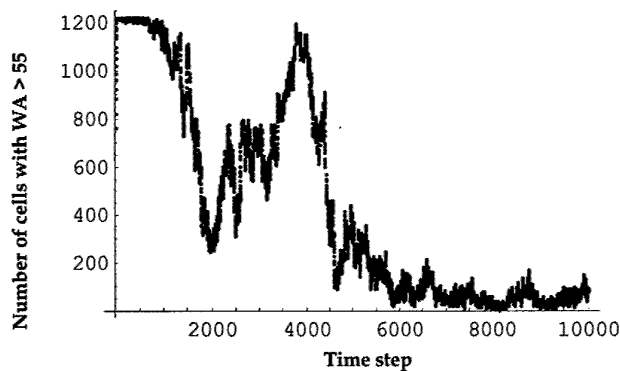

Figure 4-6:Horizontal axis plots time steps from 1 to 10000 while the vertical axis counts the number of elements that have their WA *values above the threshold value of 55 at each time step.*

One can see an initial degrading avalanche ending at time step 2000, to be followed by an upgrading avalanche which in turn is annulled by another massive degrading avalanche. To see the details let us plot this variation in parts. Figure 4-7 is a plot for the first 1000 steps.
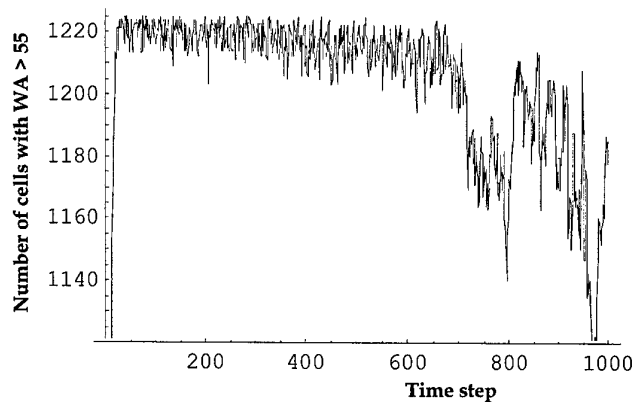
Figure 4-7: Shows in detail the first 1000 steps of the plot in Figure 4-6

The number of elements having WA values above the threshold rises steeply in the initial stages, as mentioned before, and almost all elements are above the threshold by the time step 50. Small degrading and upgrading avalanches start occurring after the time step 600. These minor fluctuations continue up to the time step 1300 when a substantial degrading avalanche occurs, see Figure 4-8. Although this avalanche is quite steep it does not have large enough magnitude to satisfy our demands. In fact it degrades the WA values of about 430 (1150-720) elements only whereas we require a deciding avalanche to affect at least 490 elements. This avalanche is annulled by a subsequent upgrading avalanche starting just after the time step 1400.

Figure 4-8: : Shows in detail the 1000 to 2000 time steps of the plot in Figure 4-6

By the time step 1500, however, the cumulative effects of *interdiction* have decidedly overcome the cumulative effects of *creativity* and *averaging* rule and a massive degrading avalanche sets in which lasts until slightly past the time step 2000. Consider the time interval [1500, 1800]. In this interval the *WA* values of 775 (1100-325) elements have fallen below the threshold gi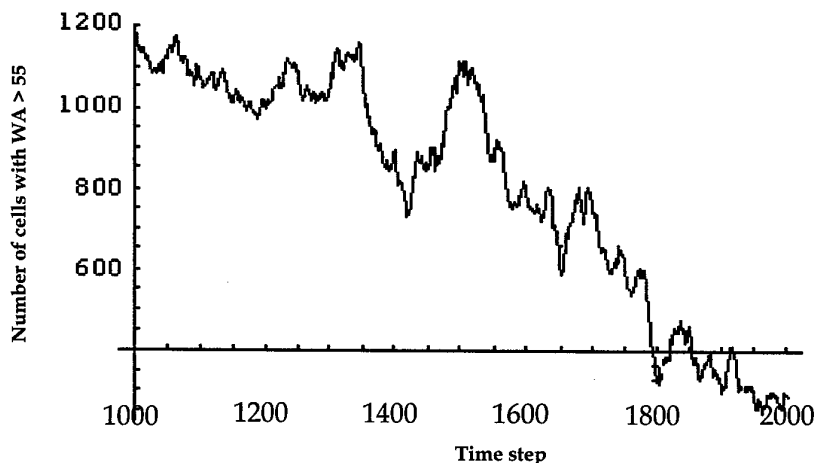ving this degrading avalanche a steepness $S \cong 2.6$. This satisfies the criteria set in H 's *strategic goal* for a deciding avalanche. It is, however, interesting to study the part of this avalanche contained in the interval [1500, 1650]. During this interval 550 (1100-550) elements fall below the threshold in their *WA* values giving this part of the avalanche a steepness $S \cong 3.7$. This part is therefore a much steeper avalanche and therefore more forceful in its impact, and although it is not as massive as the bigger one it has enough magnitude to achieve the set H 's *strategic goal*.

Hence according to our estimates the R forces would have sufficient compelling reasons to abandon hostility by the time step 1650. Although the simulation shows a massive upgrading avalanche setting off just after the time step 2000, that would not help R if it is compelled to abandon hostilities before that time step. Figures 4-9, 4-10 and 4-11 respectively show the states of the automaton at the
- time step 1500 - beginning of the avalanche,
- time step 1650 – end of the smaller but steeper avalanche and
- time step 1800 – end of the bigger avalanche.

Part B of each of these figures plots the *WA* values of individual cells in the automaton as explained before.
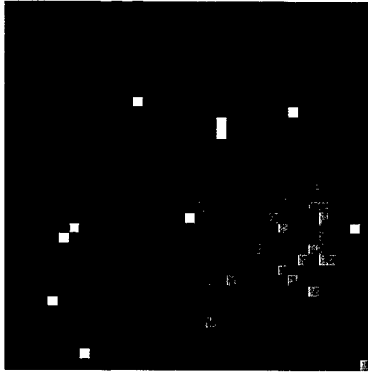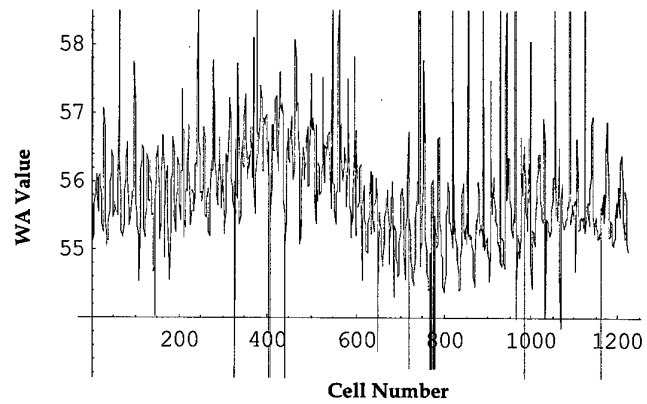
(A) (B)

Figure 4-9: (A) Configuration of the automaton and (B) WA value distribution at the time step 1500

(A) (B)

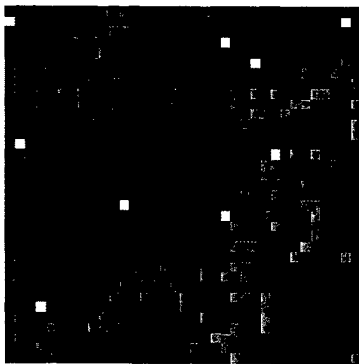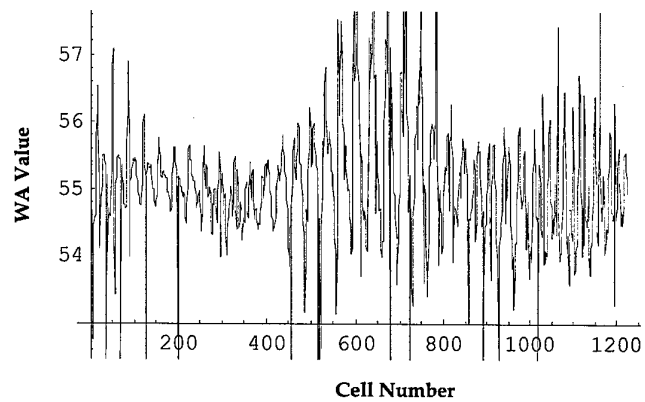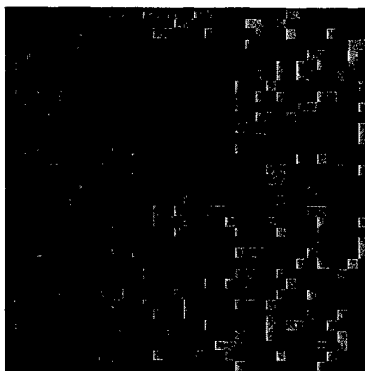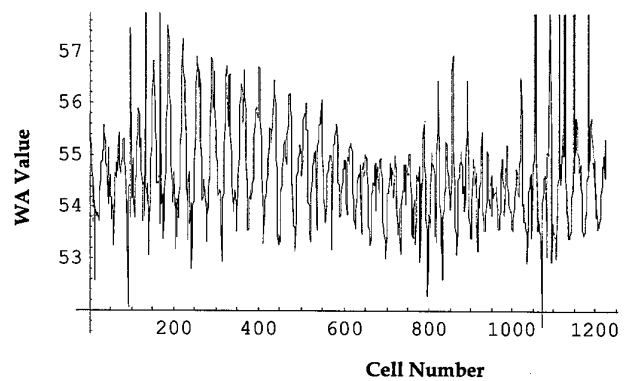*Figure 4-10: (A) Configuration of the automaton and (B) WA value distribution at the time step 1650*

(A) (B):

Figure 4-11: (A) Configuration of the automaton and (B) WA value distribution at the time step 1800

4.3.2 Quantitative results

Examination of the plots shown in Figures 4-3(E), 4-4(E) and 4-5(E) and similar plots obtained in the rest of the simulations, makes it clear that if we are looking for some particular avalanche satisfying some given characteristics, then it is not certain when such an avalanche would be found in a given run of the simulations. Hence, given a particular adversary configuration, if a deciding avalanche has not materialised in the first 10,000 time steps, then that does not imply that such an avalanche would never occur. In fact one can never rule out the possibility of a certain type of avalanche occurring. However we cannot wait forever to find out if our strategy succeeds. Let me therefore tighten the formulation of H 's *strategic goal* to read as below (see the original formulation given in Section 4.2):

Achieve a *degrading avalanche* of magnitude $\overline{M}$ = 490, with respect to the threshold WA value $\overline{T_{WA}}$ = 55, and having a steepness $\overline{S}$ ≥ 2.5, *within the first 5000 time steps*.

There is no particular reason for imposing the bound at the 5000th time step. In real situations the bound will depend upon other strategic considerations and upon how the real time maps onto the simulation time.

Analysis of a large set of simulations yielded the following results.

    i.   68% of simulations suffered degrading avalanches of magnitude greater than 490 and having steepness values greater than 2.5 before the 5000th time step.

    ii.   The above includes the 16% of all simulations that suffered degrading avalanches of magnitude greater than 490 but having a steepness value greater than 5.

    iii.   In 70% of those cases where the deciding avalanche occurred, it materialised between the time steps 1000 and 2000.

    iv.   In 8% of all simulations no degrading avalanches of magnitude greater than 490 occur at all before the time step 5000.

Hence the adopted interdiction strategy has about 68% chance of being successful. One can increase this probability of success by increasing the intensity of interdiction. This can be done by a small increase in ρ and/or a small increase in μ. Such alterations also hasten the onset of the desired avalanches. It should be borne in mind that these alterations have to be relatively small. Large alterations will result in an overkill shifting the balance between *interdiction* and *creativity* far from where we want it to be. To obtain a quantitative appreciation of this let us compare the following simulation results with different values of μ while ρ remains fixed:

a. Figure 4-12 shows yet another instance of the simulations with the interdiction parameters having values $\rho = 6.3$ and $\mu = 0.09$. Part *A* of the figure counts the number of elements having their *WA* values above the threshold value of 55. As can be seen the number of such elements never drops below the 1170 mark in the first 5000 time steps, or H *'s strategic goal* is not achieved. In fact simulations show that, with this interdiction strategy, there is less than 5% chance of obtaining a degrading avalanche that satisfies the strategic goal. Part *B* of the figure, which plots the evolution of the average *WA* value, shows that this average value suffers an initial decline before oscillating about 57 and that it never drops down to the threshold value of 55.

b. With the interdiction parameters pegged at $\rho = 6.3$ and $\mu = 0.1$, we found that the strategy has about 68% chance of being successful. It is instructive to compare the plots in Figure 4-12 with the corresponding plots in the Figure 4-3 (or Figure 4-4/4-5). Note the plot of the average *WA* value in Figure 4-3(*F*), this average value oscillates about 54.

c. Parameter values $\rho = 6.3$ and $\mu = 0.11$ quantify the interdiction strategy whose results are shown in Figure 4-13. Part *A* of the figure shows that a massive avalanche ensues around the time step 600 and by the time step 800 all but 200 elements have been degraded to a state with *WA* values below the threshold. This avalanche more than satisfies the requirements of H *'s strategic goal.* Simulations for this interdiction strategy show that such avalanches are typical, the chance of satisfying the strategic goal exceeds 95%, and that attempts at recovery are rare. Figure 4-13(*B*) shows that the average value suffers an initial decline which takes it past the threshold value before oscillating about 52.

Such significant deviations in the results, when parameters governing the simulation have been slightly altered are signatures of cumulative effects. Increasing μ from 0.09 to 0.1 means that at every time step we select a number (determined by the value of ρ) of R elements and instead of degrading their *WA* values by 9% each, we degrade them by 10% - and similarly when μ increases from 0.1 to 0.11. Although the total interdiction applied to the R system increases by a very small amount in each time step, this small increase occurs in almost every time step and accumulates over time. It is therefore not surprising that after a large number of time steps the total degradation applied to R has increased by a relatively large amount. However, I must stress that even this relatively large total degradation does not drastically shift the point of balance between H *'s interdiction* and R *'s creativity.* This is evident from the behaviour of the average *WA* value. As μ shifts from 0.09 to 0.1 and then to 0.11, the point about which the average *WA* value for the R elements stabilises shifts from 57 to 54 and then on to 52. It so happens that the threshold $\overline{T_{WA}}$ is fixed at 55 in the stipulated H *'s strategic goal.* With $\mu = 0.09$ the average *WA* value stabilises just above $\overline{T_{WA}}$ thus giving a very low probability of success with respect to the set strategic goal. While $\mu = 0.1$

drives this average *WA* value to stabilises just below $\overline{T_{WA}}$ giving a 68% chance of success and $\mu = 0.11$ drives this average *WA* value a further two points down from $\overline{T_{WA}}$ thus giving a very high probability of success This explains the seemingly large deviations in results in the comparative study above.

Changing μ significantly will of course drastically shift the point of balance between H's *interdiction* and R's *creativity*. This is illustrated in Figure 4-15 which plots the results of the interdiction strategy with $\rho = 6.3$ and $\mu = 0.15$. Part (A) of the figure shows that by the time step 400 all the elements have been degraded to a state with *WA* values below the threshold. Moreover as part (B) shows the average *WA* value stabilises about 44 which is far below the threshold $\overline{T_{WA}}$. This strategy therefore results in an overkill.

Let us now go back to the question we asked at the beginning of Section 4.2. We have now established that given the *averaging* rule and the nature of R's *creativity* as specified there, an *interdiction* strategy with $\rho = 6.3$ and $\mu = 0.1$ has a 68% chance of being successful while not being an overkill. Hence these values of ρ and μ, or very small alterations to these (to obtain a higher chance of success) quantify a *minimal strategy for interdiction*. Note that one can vary ρ and then determine a different value of μ to obtain another minimal strategy.

Figure 4-12: Results of a simulation with ρ = 6.3 and μ = 0.09. The horizontal axes represent time steps. The vertical axis in part (A) counts the number of elements that have their WA values above the threshold value of 55, and in part (B) it represents the average WA value.

Figure 4-13: Results of a simulation with ρ = 6.3 and μ = 0.11. The horizontal axes represent time steps. The vertical axis in part (A) counts the number of elements that have their WA values above the threshold value of 55, and in part (B) it represents the average WA value.

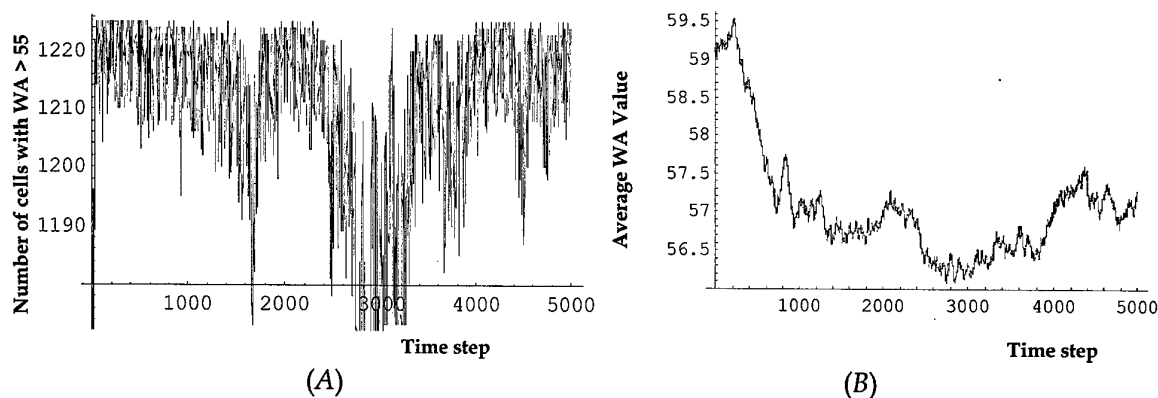*Figure 4-15: Results of a simulation with ρ = 6.3 and μ = 0.15. The horizontal axes represent time steps. The vertical axis in part (A) counts the number of elements that have their WA values above the threshold value of 55, and in part (B) it represents the average WA value*
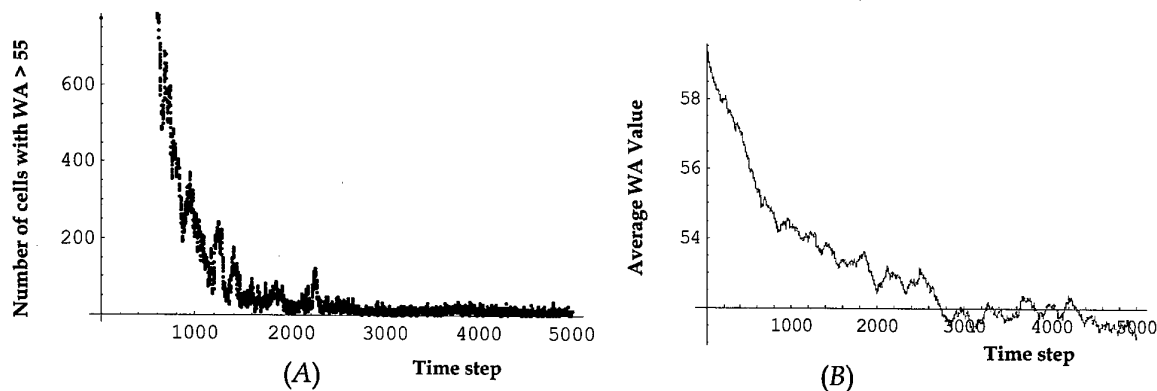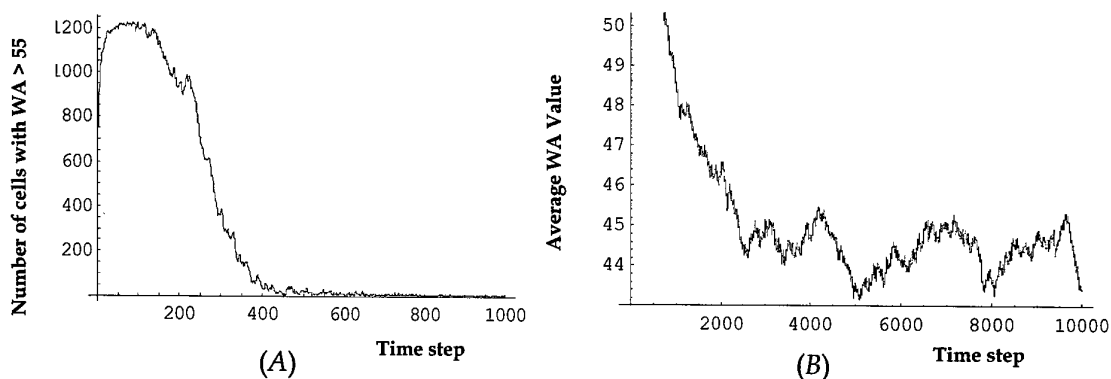
5. Conclusions

To date most EBO thinking has been largely intuitive. Proponents have put forward a number of interesting doctrines and a variety of novel strategies for this brand of planning and operations. What has however been missing is a sound framework to conduct experiments – to put these strategies to test. A framework to formulate these strategies systematically, elicit the parameters that govern these strategies, allow the parameters to be varied and thence conduct 'what if' experiments. It is only through such experimentation that one can progress from the intuitive realm to the realm of methodical study. The main contribution of this report lies in establishing that cellular automata can provide the tools needed for such experimentation. Experimentation, that can investigate the two themes that lie at the heart of any effects-based strategy which are that the strategy be holistic and that all the higher order effects of the strategy be traceable.

A lesson that one couldn't fail to learn during the analysis is that conducting EBO requires an extensive knowledge of the adversary culture across all the facets, political, military and socio-economic. Reliable values of the parameters that govern the simulations can only be gleaned from a deep understanding of the adversary system. This is not surprising and is certainly not peculiar to the methods of investigation advocated in this report; because, effects-based operations intend to establish dominance over the adversary not just in the physical domains, but more importantly in the behavioural domains also.

The simulations are also sensitive to the parameters specifying the degradation sought in the enemy system, and the parameters governing the interdiction applied to the adversary. These parameters are therefore critical in both planning and executing an EBO type operation.

The simulations that have been reported here provide a starting point. More in-depth intelligence regarding the adversary would provide more realistic simulations covering more of the behavioural domains. However the basic problem has been cracked – simulations through cellular automata provide one way to formulate EBO related questions as tractable questions in a quantitative analysis. An analyst can always conduct 'what if' experiments with plausible values for parameters representing cultural and other facets. This will provide him with a holistic understanding of various patterns of cascading effects. Patterns that vary with the type of interdiction applied, and it is these patterns that enable the analysis of any effects-based operations.

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19. ABSTRACT In this report I show how simulations through cellular automata can be used to answer Effects-Based Operations (EBO) related questions. Such simulations provide effective tools to investigate the two themes that lie at the heart of the EBO paradigm which are that (a) the operations be holistic –treat the adversary as a complex system with interconnected political, military, economic and social facets and (b) that the immediate and higher order effects of the actions be gauged and exploited. This report focuses on the effects of actions against an adversary. How to integrate the friendly national capabilities for a whole of government approach has not been discussed here. An Effects-Based strategy is formulated which is a minimal strategy in the sense that it provides a mode of interdiction whose cascading effects are strong enough to compel the enemy to abandon hostilities while not driving the adversary to a point where its military, and non-military social systems become unstable. The parameters governing this strategy are identified and simulations conducted to elicit the parameter values that produce the desired effects.